IDENTIFYING THE MECHANISMS OF CHANGE AND IN-SESSION THERAPIST FIDELITY IN MEASUREMENT BASED CARE FOR DEPRESSION

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IDENTIFYING THE MECHANISMS OF CHANGE AND IN-SESSION THERAPIST FIDELITY IN MEASUREMENT BASED CARE FOR DEPRESSION

Despite its emergence as an evidence-based practice (Glasgow et al., 2014; Scott & Lewis, 2014), there is a dearth of literature explicating *how* measurement-based care (MBC) achieves its positive effects in psychotherapy for depression. MBC involves the systematic use of client progress data to guide treatment decisions in therapy (Scott & Lewis, 2014). MBC has three key elements when applied with adherence: a) administration of a symptom measure; b) clinician and client review of symptom scores; and c) clinician and client discussion of symptom scores in session. Simply providing clinicians with feedback regarding client progress improves client outcomes (Lambert et al., 2003). Despite evidence supporting MBC's effectiveness, a gap exists in the literature regarding the process and mechanisms by which MBC acts to produce change in depression symptoms.

The present studies served to close this gap in the literature regarding how MBC is used in session and MBC's potential mechanisms of action through the use of rigorous qualitative and quantitative modeling procedures. The present studies sought to achieve the following aims: Study 1) To evaluate the variation in clinician approaches to integrating MBC into clinical sessions across treatment; Study 2) To identify patterns and trajectories of clinician MBC adherence following MBC training; and Study 3) To assess session attendance (i.e. treatment engagement) as a putative mechanism by which MBC may act to produce depression symptom change.

Study findings suggested that clinicians generally responded to MBC feedback in line with Feedback Intervention Theory (Kluger & DeNisi, 1996), but also highlighted the complexities of clinician assessment and decision-making processes. Observable patterns of clinician MBC

adherence post training also emerged, and clinicians demonstrated significant variation in their MBC use. The studies, however, failed to identify treatment engagement as MBC's mechanism of change. Although additional research is needed to elucidate MBC's causal processes, findings from the present studies may serve inform strategies to enhance implementation of MBC, improve outcomes for clients seeking psychotherapy, and reduce the burden of disease associated with depression.

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Table of Contents

Supplemental Materials - Tables

Page

Supplemental Materials - Figures

Supplemental Materials - List of Abbreviations

CO-MED = Combining Medications to Enhance Depression Outcomes

COMET = Clinical Outcomes in Measurement-Based Treatment Study

EHR = Electronic Health Record

GMM = Growth Mixture Modeling

GMM-CI = Growth Mixture Model with Class Invariant Covariances

GMM-CV = Growth Mixture Model with Class Variant Covariances

ICC = Intra-Class Correlation

LCGA = Latent Class Growth Analysis

MINC = Minimal Intervention Needed for Change

MBC = Measurement Based Care

OQ-45 = Outcome Questionnaire - 45 Item

PHQ-9 = Patient Health Questionnaire - 9 Item

STAR*D = Sequenced Treatment Alternatives to Relieve Depression Study

QIDS-C = Quick Inventory of Depression Symptomatology

Supplemental Materials – Appendices

Page

General Introduction

Depression remains one of the most impactful health conditions worldwide despite the existence of effective psychotherapy and pharmacological interventions. A 2016 report from the World Health Organization identified that nearly one in 10 individuals worldwide has a diagnosis of depression or anxiety, but that only 50% of individuals with symptoms actually receive treatment and only 40% receive effective treatment (World Health Organization, 2016). One barrier to accessing effective treatment is the substantial lag in the time between the development and empirical testing of interventions, revealing evidence based practices (EBPs), and the implementation of EBPs in community settings. In fact, in can take nearly two decades for even a small amount of research evidence about mental health interventions to move from the research "lab bench" to clinical application (Balas & Boren, 2000). Even when EBPs for depression are implemented in the community, they typically require substantial training and ongoing supervision and face numerous barriers to sustained use (e.g. clinician attitudes, low resources; Jensen-Doss & Hawley, 2010; Lewis & Simons, 2011; Stewart, Chambless, & Baron, 2012; Stirman et al., 2012). Researchers have begun to explore minimal interventions needed to promote depression symptom change (i.e. MINCs; Glasgow et al., 2014) that are easily implemented in resource-strained community mental health settings. Identification of these MINC's may enable the implementation of only the core components of EBPs (i.e. the components that maximize symptom change) in order to maximize reach, reduce burden on clinicians, and enhance outcomes for community clients with depression.

Definition and Evidence Supporting Measurement-Based Care

Measurement-based care (MBC) is an EBP that is conceptualized as a MINC, with potential for far reaching impact on the global burden of depression. MBC can be defined as a “feedback intervention” that involves the systematic use of client progress and outcome data, typically assessed by self-report prior to each clinical encounter, to guide treatment decisions in therapy sessions (Scott & Lewis, 2014). MBC has appeared in a number of formats in the literature from paper and pencil self-report measures to technologically advanced, electronic Measurement Feedback Systems that provide real-time graphs of client progress and clinical decision support (Lyon & Lewis, 2016). MBC is also known by many other names, including progress monitoring (Byrne, Hooke, Newnham, & Page, 2012; Goodman, McKay, & DePhilippis, 2013; Newnham, Hooke, & Page, 2010; Persons, Koerner, Eidelman, Thomas, & Liu, 2015), outcome monitoring (De Jong et al., 2014; Young, Grusky, Jordan, & Belin, 2014), and feedback systems (Connolly Gibbons et al., 2015; Kelley & Bickman, 2009). All of these names share a common thread of the use of psychometrically validated assessment tools to evaluate and enhance therapy progress and outcome.

Simply having clinicians administer a self-report questionnaire and independently review client scores improves outcomes for clients (Lambert et al., 2003). However, the impact of MBC is enhanced if the clinician reviews the symptom scores and provides feedback to the client about therapy progress via discussion in therapy (Lambert et al., 2005). Some of the earliest emerging evidence pointing to MBC’s effectiveness in psychotherapy came from Lambert and colleagues' (2005) work using the Outcome Questionnaire-45 (OQ-45) measurement feedback system. The OQ-45 measures symptom distress, interpersonal relationships, and social role functioning, and the feedback system enables the identification of clients as “on track” or “not on track” to improve in psychotherapy (Lambert & Finch, 1999). Lambert and colleagues’ meta-analysis of four studies exploring the effectiveness of the OQ-45 suggested that providing feedback to clinicians about client progress increased client session attendance, reduced deterioration, and enhanced psychotherapy outcomes, especially for clients identified by the OQ-45 measure as not on track to improve (Lambert et al., 2003; Whipple et al., 2003).

Since Lambert and colleagues (2003) seminal work, numerous studies have emerged providing evidence for MBC's clinical effectiveness in reducing deterioration, improving outcomes, enhancing therapeutic relationships, and reducing treatment readmission for individuals seeking treatment for depression (Byrne et al., 2012; Crits-Christoph et al., 2012; Fortney et al., 2016; Guo et al., 2015; Lambert et al., 2005; Newnham et al., 2010; Probst et al., 2013; W. Simon, Lambert, Harris, Busath, & Vazquez, 2012). For example, MBC implementation using the OQ-45 in individual psychotherapy resulted in reduced clinical deterioration in a sample of inpatient clients with comorbid depressive disorders and somatoform disorders (Probst et al., 2013). Evidence also supports MBC's effectiveness in enhancing psychotherapy outcomes for depression and anxiety disorders in both children and adults (Elmquist, Melton, Croarkin, & McClintock, 2010; Newnham et al., 2010), and for identifying and monitoring clients at high risk of self harm and suicidal ideation (Restifo, Kashyap, Hooke, & Page, 2015). MBC may be beneficial in both short and long term therapies (De Jong et al., 2014) and youth and family therapy (Bickman, Kelley, Breda, de Andrade, & Riemer, 2011), though more research is needed to better understand the impact of MBC on long term treatment outcomes (De Jong et al., 2014).

MBC has also been shown to enhance psychotherapy outcomes across a variety of client presenting problems beyond depression, including substance abuse (Crits-Christoph et al., 2012; Goodman et al., 2013) and eating disorders (Simon et al., 2013), among others. In addition, MBC has evidence supporting its use as a tool for both clinician professional development and for ongoing quality assurance at the organization level through the use of aggregate MBC symptom change data to evaluate treatment effectiveness (Fortney et al., 2016; Scott & Lewis, 2014).

Overall, there is robust and consistent evidence supporting MBC's effectiveness as an EBP for a wide range of client presenting problems.

MBC has also been studied extensively in pharmacotherapy as a method for providing physicians with feedback and clinical decision support regarding medication dosages and side effects for depression treatment. Trivedi and colleagues (2007) explored the clinical utility of MBC in their Sequenced Treatment Alternatives to Relieve Depression study (STAR*D), which aimed to evaluate the effectiveness of citalopram (a selective serotonin reuptake inhibitor) for remitting the symptoms of major depressive disorder. In the STAR*D trial, the Quick Inventory for Depressive Symptomatology (QIDS-C; Rush et al., 2003) and client ratings of side effect frequency, intensity, and burden served as the basis for MBC at each medication management visit. Physicians then automatically received feedback on symptom and side effect changes as well as optimal treatment adjustments (e.g. dosage of medication). MBC was ultimately effective for encouraging physicians to follow treatment recommendations at 85% of medication management visits with clients (Trivedi et al., 2007). Trivedi and colleagues suggested that the MBC approach may have had a positive impact on treatment effectiveness and depression remission rates through the mechanism of encouraging more accurate and timely dosage changes for clients (Trivedi et al., 2006, 2007).

More recent randomized controlled trials (RCT) provided additional support for Trivedi and colleagues' (2007) work by comparing antidepressant medication management plus MBC to antidepressant treatment as usual. For example, Yeung and colleagues (2012) Clinical Outcomes in Measurement-Based Treatment (COMET) study found that clinicians who received monthly updates on client depression symptoms had clients who were more likely to respond to antidepressant medication and experience remission of symptoms in a primary care setting (Yeung et al., 2012). In a separate RCT, Guo and colleagues (2015) also found that the clients receiving MBC alongside their medication management in outpatient treatment had better overall symptom improvement and improved more rapidly than those not receiving MBC. They also identified that clinicians who received MBC had higher rates of dosage adjustments in order to achieve the most effective medication dosage throughout treatment (Guo et al., 2015).

In summary, MBC appears to be highly effective not only for tracking client progress in psychotherapy, but also for enhancing optimal medication dosage identification and more rapid dosage changes to maximize pharmacotherapy effectiveness. MBC's effectiveness in pharmacotherapy provides insight into MBC's potential mechanisms of action (i.e. more effective medication dosage), however additional research is needed in both psychotherapy and pharmacotherapy to identify how MBC works to produce change.

Core Components of MBC and MBC Adherence

There is substantial evidence supporting MBC as an effective intervention for promoting symptom change in both psychotherapy and pharmacotherapy. MBC's treatment-enhancing effects appear to cut across diagnoses (e.g. depression, substance use), clinical settings (e.g. primary care, inpatient hospitals), and treatment formats (e.g. individual, couples). MBC appears to be most effective when feedback information is shared with both clinician and client, though treatment gains still occur when the clinician does not discuss symptom scores with the client (De Jong et al., 2014; Lambert et al., 2005). These findings raise important questions regarding the core components of MBC and the dosage of these components required to achieve depression symptom reduction. Based on the extant literature, our research team has articulated three key elements that are required for clinicians to demonstrate adherence to MBC: a) administering an empirically validated symptom measure (i.e. a self-report questionnaire) at the beginning of each clinical session; b) clinician (and client) review of symptom measure scores and score trajectories over time (if available); and c) clinician discussion of symptom scores with the client in session (Lewis et al., 2015).

Research has yet to identify the dosage of these three components (i.e. administer, review, and discuss) required across psychotherapy treatment in order to observe enhanced outcomes. Many existing studies of feedback systems assume that clinicians use MBC at every session, and these studies either fail to discuss variability or note significant variation in clinician self reported MBC use. While it is clear that administration of a measure is a core component of MBC, much remains unknown about the frequency of administration truly needed to promote symptom change. Since many MBC effectiveness studies do not rely on clinicians to administer symptom measures at each session (e.g. by using research specialists or site administrative staff; Connolly Gibbons et al., 2015; Crits-Christoph et al., 2012; Lambert et al., 2005), it is not yet clear how frequently clinicians would choose to administer MBC measures and the impact that variable administration might have on outcomes. Given that Dowrick and colleagues (2009) suggest that the administration process may be key to client self-reflection on symptoms, more research is needed to determine at what minimal frequency measures must be administered to drive MBC's effects.

A second consideration regarding the core components of MBC is the degree to which score review may be core to MBC's effects. In a study of MBC in an urban community mental health setting, 89% of clinicians reported always reviewing score information (Connolly Gibbons et al., 2015). In contrast, a study by Bickman and colleagues (2016) reported that clinicians accessed symptom scores for 45% to 71% of various administered measures for youth receiving outpatient psychotherapy. However, simply accessing MBC score information does not necessarily imply that the clinician actually reviewed the scores. Bickman and colleagues (2016) also report enhanced treatment outcomes with increased clinician MBC administration and review, though these results were specific to one specific clinic. In summary, the literature reflects significant variability in the degree to which clinicians choose to review symptom scores for each clinical session. Despite variability in review frequency, these studies still showed enhanced treatment outcomes with MBC administration for clients receiving psychotherapy for depression and other clinical diagnoses (Bickman et al., 2016; Connolly Gibbons et al., 2015). Additional research is needed to evaluate the degree to which review of symptom scores is core and the frequency of score review that is necessary to achieve enhanced depression symptom change.

Finally, results in the MBC effectiveness literature suggest that discussion of client progress between clinician and client in session enhances outcomes above and beyond simple score review (Lambert et al., 2003). However, over half of clinicians (57%) in Lambert and colleagues (2001) research reported only sometimes, rarely, or never choosing to discuss symptom score information with their clients. Gibbons and colleagues (2015) reported that 67% of clinicians reported discussing symptom scores with clients (Connolly Gibbons et al., 2015). The clinicians that chose to discuss MBC reported using it to inform treatment plans, change therapy approaches, change the problem focus, or review clinical books and materials (Connolly Gibbons et al., 2015). The limited literature on discussion appears to indicate substantial variability in both clinicians decisions to discuss MBC scores and the impact of these discussions on treatment. However, many studies fail to assess how frequently clinicians discuss MBC in session, and those that do often rely on retrospective clinician self-report of discussion at a single time point. Even fewer studies report details about the content of discussion in session and how MBC impacted treatment, two elements of MBC application that may drive symptom change. As with the other two components of MBC that may be "core" (i.e., administration and review of scores), more exploration is needed to evaluate how often discussion should occur, and what type of discussion (e.g. clinician and client reflecting on change, discussing treatment plan changes, setting new treatment goals) is needed to promote symptom change.

Despite significant support for MBC's effectiveness as an intervention, many questions remain unanswered regarding how MBC works to optimize outcomes for depressed clients. First, it is necessary to better understand the dosage of MBC elements (administration, review, discussion) that is critical to MBC's effectiveness. This may be explored by evaluating the relation between clinician use of these three MBC components and clinical outcomes to determine whether and how much of each are needed to enhance symptom change. Second, more research is needed to identify whether and how clinicians use MBC to change treatment when they do opt to review and discuss scores with the client in the therapy room. These insights regarding clinician session-by-session MBC use may shed light on its core components and mechanisms of action, thereby facilitating recommendations for the broad implementation of MBC.

The Present Studies

The present studies expanded upon previous literature by characterizing the variation in clinician approaches to integrating MBC into clinical sessions across treatment through qualitative and quantitative methods. The present studies sought to achieve the following aims: Study 1) To evaluate the variation in clinician approaches to integrating MBC into clinical sessions across treatment; Study 2) To identify patterns and trajectories of clinician MBC adherence following MBC training; and Study 3) To assess session attendance (i.e. treatment engagement) as a putative mechanism by which MBC may act to produce depression symptom change.

The present studies served to close a gap in the literature regarding how MBC is used in session, dosage of MBC required, and the potential mechanisms of action of MBC for enhancing clinical outcomes through the use of rigorous qualitative and quantitative modeling procedures. These studies will be some of the first to elucidate how MBC functions in session to engender improvements in adult client depression symptoms. Findings from the present studies may serve to identify the core elements of MBC that must occur and how often, which may ultimately inform efforts to widely implement MBC, enhance outcomes for community clients, and reduce the burden of disease associated with depression.

General Methods

Parent Study Aims and Design

The present studies were explored by leveraging data from 10 of 12 sites engaged in a four-year NIMH-funded R01 pragmatic randomized implementation trial (RCT; Lewis et al., 2015). The parent R01 sought to compare standardized and tailored approaches to MBC implementation using the Patient Health Questionnaire-9 item depression symptom self-report questionnaire (PHQ-9; Kroenke, Spitzer, & Williams, 2001) within Centerstone, the nation's largest provider of behavioral health services. The aims of the parent R01 study include: a) comparing the effect of standardized versus tailored MBC implementation on clinician-level implementation and client-level symptom outcomes; b) identifying contextual mediators of MBC adherence; and c) exploring the differential impact of MBC adherence in the two implementation conditions on client outcomes.

Implementation Conditions

To achieve these aims, 12 Centerstone sites across two states (Indiana and Tennessee) were randomized to either standardized or tailored implementation approaches. The standardized implementation sites completed a baseline assessment, four-hour MBC workshop, and hour-long triweekly consultation meetings that focused on maximizing clinician MBC adherence (i.e. PHQ-

9 administration at each session, review of PHQ-9 scores, and discussion of the PHQ-9 in session). Conversely, sites randomized to the tailored implementation condition completed the baseline assessment and customized four-hour MBC workshop followed by triweekly implementation team meetings. These implementation team meetings established a guideline for frequency of MBC use at each site, whereas standardized sites were instructed to use MBC each session. Additionally, implementation teams focused on identifying site-specific contextual barriers to MBC implementation and generating targeted implementation strategies (e.g. distributing educational materials, making changes to MBC procedures; Powell et al., 2015) to reduce the impact of these barriers and maximize MBC use (see Lewis et al., 2015). To increase the feasibility of the R01 study, workshop trainings were conducted in four cohorts (number of sites in each cohort: 2, 4, 4, 2) spaced five months apart to support active implementation. The 12 clinics were matched on size and rural/urban status and then randomly assigned first to training cohort and second to implementation condition.

Data Collection and Assessment Procedures

Data collection. After receiving MBC workshop training, each of the sites began a five-month active implementation period followed by 10 months of sustainment. Standardized consultation and tailored implementation team meetings were held during the five-month active implementation period. Clinicians then completed a follow up assessment at five months following training, and then began the sustainment period of 10 months to evaluate continued use of MBC. Exit interviews were conducted with a sampling of clinicians at 10 months following training (i.e. five months after the end of active implementation), and clinicians completed an additional follow-up assessment at 15 months post training (i.e. after active implementation and sustainment is complete). Data were also collected on clinician session-by-session PHQ-9 completion and MBC adherence. Additionally, approximately three clients per clinician were enrolled in the study and were assessed by research staff at baseline and treatment week 12 using the PHQ-9.

EHR modifications. The use of MBC was facilitated for clinicians through several alterations to the Electronic Health Record (EHR) systems across all 12 sites. First, clients who presented to the site with symptom of depression were flagged in the EHR as being on the depression pathway. Intake staff, study research staff, or clinicians could enroll clients in the pathway. This depression pathway indicator served as a clinical decision support tool that allowed clinicians to identify the clients with depression for whom MBC with the PHQ-9 would be most appropriate. Throughout the active implementation and sustainment period, clinicians were asked to report on their use of the PHQ-9 by entering the scores into the modified EHR. The EHR automatically graphed the clients score trajectories over time, enabling clinicians to observe changes in PHQ-9 scores over the course of treatment. In addition to PHQ-9 score entry, clinicians in Tennessee also indicated whether they viewed the PHQ-9 score trajectory graph or discussed the PHQ-9 in session by checking boxes on their electronic progress notes. Clinicians in Indiana automatically received credit for viewing the score trajectory each time they accessed the graph due to differences in EHR software. Like Tennessee, Indiana clinicians also had to check a box in the EHR to indicate that they discussed the PHQ-9 in session. In the event that the PHQ-9 was not completed during a session, clinicians in both states were asked to check a box on their progress note indicating why the PHQ-9 was not completed (e.g. time limitations, technology problems, PHQ-9 not relevant or helpful). In both states, these MBC related questions in the EHR were optional.

The main clinician-level outcome pulled from the parent R01 for the present studies was clinician-reported MBC adherence data collected in the EHR: a) PHQ-9 completion (yes/no); b) review of score graph (objectively collected in IN and subjectively reported yes/no in TN); and c) discussion of scores in session (yes/no). The main client-level outcome was change in depression symptoms per the PHQ-9 measure at baseline (beginning of treatment), treatment week 12 as reported in a phone interview, and at the end of active implementation (treatment month 5 data pulled from the EHR).

It is important to note that data for the present studies did not include implementation condition (i.e. standardized or tailored) as a variable of interest because the studies sought to answer specific questions about the variation in MBC implementation within the clinician-client dyad. Since MBC was used in clinical sessions at each site regardless of the implementation approach, all data was integrated across conditions to maximize data variation and power.

Participants

Clinicians. Clinicians providing individual psychotherapy to adult clients for whom depression was a treatment focus at the 12 randomized Centerstone sites were recruited for participation in the parent R01 study and explored in the present studies. Quantitative data for the present studies included clinicians from cohorts one, two, and three (10 sites) from the parent R01, while qualitative data included clinicians from the six sites in cohorts one and two given the dynamic nature of the parent R01 design and the timing at which clinicians completed the exit interviews (i.e., in the sustainment phase 10 months after MBC training).

Clients. Adult clients just beginning or continuing ongoing individual psychotherapy for depression with an enrolled clinician were eligible for participation in the parent R01 study. All clients included in the present studies were enrolled on the Centerstone depression pathway, an initiative that provides clinicians with a clinical decision support tool to identify clients for whom MBC with the PHQ-9 would be appropriate. To be part of the depression pathway, clients needed to have a depression diagnosis (i.e. major depressive disorder, dysthymic disorder, depressive disorder NOS, adjustment disorder with depressed mood; see Appendix B). A subset of depression pathway clients was formally enrolled in the parent R01 study (approximately three clients per enrolled clinician). To be formally enrolled, clients had to be age 18 and above, have received a depression diagnosis, have a PHQ-9 total score > 9 on a research specialist administered phone screen, have received individual psychotherapy during the study enrollment period, and had to be fluent in English. Clients were excluded if they could not provide verbal consent (e.g. due to inability to read, severe mental illness). Clients formally enrolled in the study consented to provide demographic information and baseline and week 12 PHQ-9 symptom data (see Appendix A for list of all study measures).

General Measures

Clinician and client demographics. Demographic information was collected from both clinicians and clients at baseline assessment, with additional demographic variables pulled from Centerstone Human Resources or the EHR. Clinician demographic variables included: gender, age, race, ethnicity, highest degree attained, licensure status, current status as a clinical supervisor, frequency of clinical supervision, primary theoretical orientation, years of experience as a therapist, and number of clients seen. Client demographic variables included: gender, age, race, ethnicity, sexual orientation, relationship status, employment status, occupation, years of school completed, educational level, number of children, number of children living at the primary residence, number of individuals living in the primary residence, and native language. Several of these demographic measures were included as predictor or control variables in the present studies.

Client symptom data (PHQ-9). The PHQ-9 is the most widely used, psychometrically validated measure of depression symptoms (Kroenke et al., 2001). The PHQ-9 is a 10-item depression symptom self-report questionnaire that is sensitive to weekly changes in depression symptoms (Löwe, Kroenke, Herzog, & Gräfe, 2004), with increases in total scores indicative of higher severity symptoms. Clients respond to nine questions about their depression symptoms that map onto the core symptoms of depression in the Diagnostics and Statistics Manual (DSM; APA, 2013) over the past two weeks using a Likert scale of "0 not at all" to "3 nearly every day. The measure also includes a tenth item that inquires about the degree to which symptoms have led to impairment in role functioning. PHQ-9 scores are computed by summing the scores from each of the nine symptom items. Total scores may be indicative of minimal depression (score range from zero to four), mild depression (scores five to nine), moderate depression (scores 10 to 14), moderately severe depression (scores 15 to 19), or severe depression (scores 20 to 27). A five-point change in PHQ-9 total score is indicative of clinically significant change in symptoms (Kroenke & Spitzer, 2002), and clinicians received training to use this five point change in symptoms (or lack thereof) to guide treatment. The PHQ-9 was employed in two ways for the present studies: a) for clinicians to use in each session for MBC to obtain weekly symptom severity scores; and b) to measure change in client depression symptom severity at baseline, week 12 (via telephone assessments with research specialists) and at the end of the active implementation period (via EHR).

Clinician reported MBC adherence. MBC adherence was measured using clinician-reported adherence data collected in Centerstone's EHR system within the client progress note for each therapy session. A "0" response for adherence indicates that the PHQ-9 was not completed. PHQ-9 adherence was coded as a "1" if client PHQ-9 score data were entered into the EHR. If client PHQ-9 score data were entered and the clinician only reviewed or discussed the PHQ-9 scores, PHQ-9 adherence was coded as a "2." Adherence was coded as a "3" if scores were entered, reviewed, and the clinician reported discussing the PHQ-9.

Data Screening and Missing Data

All quantitative analyses employed a maximum likelihood procedure where possible to include all available data and avoid listwise deletion of cases. Multiple imputation was employed to account for missing data in covariates to be included as independent variables in quantitative study regression models. Twenty data sets were generated using Markov chain Monte Carlo in Mplus statistical software to identify plausible values for imputation (Tihomir Asparouhov & Muthén, 2010; Schunk, 2008). All quantitative analyses were completed with the average of all 20 imputed data sets.

Chapter 1: Study 1 Introduction

Although it appears that providing feedback to both therapists and clients about client progress is optimal for enhancing treatment (Lambert et al., 2005), research has yet to identify how this feedback process informs clinician behavior in the clinical session to create depression symptom change. For example, clinicians may use MBC feedback as it is used in pharmacotherapy to inform treatment plan changes and selection of more effective treatment interventions. Alternatively, clinician discussion of symptom scores in session may enhance client engagement by actively attending to client treatment progress while simultaneously improving reciprocal understanding of symptoms. However, it is not well understood how receiving MBC feedback about client progress impacts clinicians' behavior in session.

Feedback Intervention Theory

One theory that may inform clinician in-session response to feedback is Feedback Intervention Theory (FIT; Kluger & DeNisi, 1996). The FIT is an integration of established basic self-regulation theories including goal setting theory (Locke & Latham, 2002) and control theory (Carver & Scheier, 1982), which both suggest that individuals are motivated to resolve discrepancies between personal goals and current behavioral performance. FIT posits that in order to maximize reward, individuals are likely to shift their attention to their behavior when they receive feedback that there is either a gap between their current performance and an established standard of performance (negative feedback), or that they are performing well (positive feedback). This attention on the "self" is then theorized to produce affective change and arousal (e.g. anxiety for negative feedback or excitement for positive feedback), ultimately resulting in motivation to reduce the gap between personal performance and the standard (negative feedback) or to set a higher performance standard (positive feedback).

In addition to feedback responses noted above, FIT theory highlights more nuanced responses to feedback that depend upon the characteristics of the behaviors required to enhance performance (Kluger & DeNisi, 1996). For example, an individual may be more likely to improve their performance on a task if behavior change is in line with their personal goals, if the individual feels efficacious in implementing the behaviors, and/or if the behaviors are likely to actually result in improved performance (DeNisi & Kluger, 2000). If these three conditions are not met, feedback may not result in increased motivation or behavior change. Instead, FIT suggests that when a feedback intervention highlights that an individual is either performing poorly (negative feedback) or well (positive feedback), he or she may engage in any of the following four behaviors: a) the individual can change his or her behavior to improve performance; b) he or she can abandon the standard of performance if behavior changes are unlikely to improve performance; c) he or she can modify the standard to reduce or increase expectations for performance; or d) he or she may reject the feedback provided and make no behavioral changes (Kluger & DeNisi, 1996).

MBC as a Feedback Intervention

FIT has commonly been evaluated in management and business settings as a theory to guide feedback interventions provided to employees regarding their task performance at work. For example, FIT has been used to evaluate employee behavioral responses to feedback regarding absenteeism at work (Gaudine & Saks, 2001), and general work performance (Kluger & DeNisi, 1996). To our knowledge, the FIT model has yet to be explored in the context of a mental health intervention like MBC. MBC may be conceptualized as a feedback intervention as it can highlight gaps between actual and expected client depression symptom change in psychotherapy. In the case of MBC, the clinician's performance is reflected in the client's actual symptom improvement in therapy, while the standard refers to the expected symptom change after a certain amount of time in treatment. For example, clinicians participating in the parent R01 received training that a five-point change in symptoms on the PHQ-9, either up or down, is considered clinically significant and may warrant changes to treatment (Lewis et al., 2015). Alternatively, studies by Lambert and colleagues have compared individual client progress to national norms of change on the OQ-45, thereby providing a standard of change to which clients are compared (Lambert et al., 2003).

Once a client standard of change is established, MBC provides feedback to clinicians to highlight when clients are not making progress or are deteriorating in treatment (i.e. negative feedback) or when client symptom change meets or exceeds expectation (positive feedback). MBC feedback appears to be especially helpful in cases where the feedback is negative, as it enhances outcomes most effectively for clients not making progress (Lambert et al., 2001, 2005). Regardless of whether feedback is positive or negative, FIT predicts that clinicians may be prone to select one of the following behavioral approaches: a) make a change to the treatment or session plan (change behavior); b) expect that the client is unlikely to improve or has improved enough and do nothing (reject the standard); c) expect a unique rate of improvement for a client and adjust goals (change the standard); or d) decide that the MBC feedback is inaccurate and do nothing (reject the feedback; Kluger & DeNisi, 1996).

While FIT may provide useful insight into how clinicians use MBC, extant work using FIT emphasizes the impact of feedback only on individuals' behavior. In contrast, a therapy session involves the clinician-client dyad, therefore client responses to both feedback and the clinician's behavior may also play a role in the effectiveness of MBC. For example, a clinician who discusses MBC scores in session and uses them to make changes to the treatment plan may have clients who are more engaged in treatment and who attend more sessions (Eisen, Dickey, & Sederer, 2000). In contrast, a clinician may struggle to make changes to the focus of a session if the client is unwilling to make behavioral changes or believes that the feedback is inaccurate. Further exploration of the FIT's potential for explaining how MBC is used in mental healthcare and how MBC impacts both clinician and client behavior has been recommended in the literature (Carlier et al., 2012; Lyon & Lewis, 2016). However, additional research is needed to formally test the utility of the FIT model for explaining the variation in clinician behavior resulting from using MBC, as well as the impact of this behavior change on client symptom outcomes.

The Present Study

The present study will leverage data from the parent R01 trial (see details above) to close a gap in the literature regarding how MBC is used in session and the degree to which the FIT model can accurately capture clinicians' in-session MBC behaviors. The present study will employ qualitative analytic methods to evaluate variation in clinician approaches to integrating MBC into clinical sessions across treatment (Study 1 aim). It may also promote better understanding of how clinicians approach clinical decisions based on the nature of feedback (positive or negative), and identify the degree to which an individual behavior change theory like FIT can capture these decision making processes. Additionally, results of this study may have implications for understanding the degree to which different clinician behavioral responses to feedback result in enhanced outcomes for clients, thereby highlighting additional putative mechanisms of action to be tested in future research efforts.

Hypotheses

It was anticipated that clinicians would employ MBC in line with FIT model and would change their behavior, reject the feedback, reject the standard of symptom change, or change the standard of symptom change upon receiving feedback about client progress from MBC (Kluger & DeNisi, 1996). These responses to feedback were expected to vary based on the sign of the feedback (i.e. positive or negative), such that clinicians who receive feedback showing the client is making progress (positive feedback) may choose to not change their behavior, but also may not reject the feedback (i.e. because they agree with the feedback that the client is making progress). In these cases, it is hypothesized that some clinicians may diverge from the FIT model responses such that they accept the feedback as accurate but choose not to make changes to their behavior or the standard of symptom change as they believe the client has made adequate progress and no changes are required.

Study 1 Methods

Participants

Clinicians were selected for exit interview participation from six of the 12 participating clinic sites. These sites were selected due to the timing of the parent R01 cohort design, as only six clinic sites had reached the 10 month post MBC workshop training timeline required for exit interview participation. Clinicians were eligible for participation in the exit interview if they had completed MBC workshop training and follow-up surveys at five months post training (total clinician $N = 51$). The recruitment goal was to select approximately six clinicians per site for exit interviews using purposeful sampling, or the systematic selection of participants based on research questions (Palinkas et al., 2013). In the present study, purposeful sampling was to be achieved by identifying and completing exit interviews with equal numbers of clinicians with "low," "medium," and "high" MBC use in order to capture the full range of ways in which MBC was implemented among clinicians (Palinkas et al., 2013). However, difficulties in successful recruitment of clinicians and lack of availability of MBC use data from the EHR in the recruitment timeline resulted in the need to reach out to all eligible clinicians for participation and categorization of "low," "medium," and "high" use clinicians after completion of the exit interviews. The final sample of completed exit interviews included two to four clinicians from each site and a final *N* of 16 clinicians. The sample of enrolled clinicians included therapists, psychiatrists, interns, and clinical supervisors. See Table 1 below for number of eligible and recruited clinicians across sites.

Table 1. Distribution of exit interview eligible and participating clinicians across sites.

Site	Eligible Clinicians	Participating Clinicians
1	9	1
2	15	5
3	6	1
4	9	3
5	7	4
6	5	2

Measures

Exit interviews. Qualitative data was collected through a series of one-on-one, semi-structured exit interviews, which took place approximately 10 months (range of 9-13 months) following completion of MBC workshop training. All interviews were conducted by phone by a trained research specialist and lasted between 30 minutes and an hour. The study PI (Scott) trained two post-baccalaureate research specialists to conduct the exit interviews. Training involved an initial meeting to review exit interview questions, followed by the research specialists completing mock interviews with at least two study staff unfamiliar with the exit interview content. The study PI then reviewed each of the mock interviews and met with the research specialists to provide group feedback regarding interviewing skills. The research specialists were also trained in confidentiality procedures and in techniques for handling clinician distress prior to completion of the interviews. Specifically, they were trained to validate clinicians' concerns, to reaffirm that participation in the interview is voluntary, and to discontinue interviews in the event that clinicians withdraw consent or become distressed, though the likelihood of the latter is low given the nature of the interview content. The study PI reviewed two additional interview recordings approximately two months into the interviewing process to provide ongoing feedback on interview implementation. The interviews were recorded using BlueJeans conference call recording software and subsequently submitted to a professional company for transcription.

The FIT-guided questions in the interview consisted of four multiple-choice scenarios that asked clinicians to select both a quantifiable response (i.e. A, B, C, or D) and provide an example of why they selected their response. The questions inquired about the subject's typical response to situations in which they received PHQ-9 scores showing that their client was deteriorating (feedback sign: negative), making progress (feedback sign: positive), or not making progress (feedback sign: negative). The response choices that were provided were based on the behavioral responses predicted by FIT, which suggests that the clinicians can respond to feedback in one of four ways: a) change their behavior to improve outcomes by making a change in the treatment plan; b) reject the standard of change expected for their client and do nothing (e.g. they believe that the client is unlikely to improve/they believe the client has improved enough); c) change the standard (e.g. they expect the rate of client improvement to be unique); or d) reject the feedback and do nothing (e.g. they believe that the PHQ-9 feedback is inaccurate) (Kluger & DeNisi, 1996). An "other" option was also offered to clinicians in order to provide them the opportunity to report a behavioral response that fell outside of those predicted by FIT. After selecting a response, subjects were probed by the research specialist to provide details about the reasoning behind their choices (see Table 2 for FIT questions).

MBC Use Level. Following completion of clinician exit interviews, MBC penetration data (i.e. percentage of sessions where PHQ-9 was administered to clients out of those sessions where PHQ-9 could have been administered) and adherence data (i.e. whether clinicians administered, reviewed, and/or discussed the PHQ-9 at each therapy session with clients) were examined to identify clinicians as "low," "medium," and "high" MBC users (see Participants section above for more details). Mean penetration and adherence scores were obtained for each clinician based on their monthly PHQ-9 penetration and adherence data for all depression pathway clients collected over the five-month active implementation period (five months after receiving training in MBC). To compute average penetration, the number of PHQ-9s completed by each clinician was compared to each clinician's possible PHQ-9s that could have been completed for eligible clients over the five-month period. This calculation was multiplied by 100 to obtain a percent and was reported as an average percent penetration value for each clinician.

To compute average adherence, a MBC adherence score of "0" (no PHQ-9 completed), "1" (PHQ-9 completed only), "2" (PHQ-9 completed and score either reviewed by clinician or discussed in session), or "3" (PHQ-9 completed, reviewed by clinician, and score discussed in session) was assigned to each therapy session for which adherence data was available for all depression pathway clients. Average adherence scores were then computed by averaging all session adherence scores and then dividing by the total number of therapy sessions completed. This calculation resulted in each clinician receiving an average adherence score ranging from "0," or low adherence, to "3," high adherence.

A tercile split was then performed on both the penetration and fidelity data to categorize each of the participating clinicians as "low," "medium," or "high" MBC users based on the convergence of the penetration and adherence data (i.e. clinicians who score low, medium, and/or high on both penetration and adherence will be categorized as "low" "medium" or "high," respectively). In the event that the penetration and adherence data did not converge, clinicians were assigned to the group that would minimize overestimation of use (i.e. "high" on penetration and "medium" on adherence would result in assignment to the "medium" group). This measure of MBC use enabled the contextualization of differences in the qualitative exit interview data that resulted from clinician variability in MBC application (i.e. high use clinicians having unique responses to questions compared to low use clinicians).

Qualitative Coding Procedures

Initial coding procedure and establishing inter-rater reliability. Transcripts from the exit interviews were coded using qualitative content methods and reflexive team analysis (Graneheim & Lundman, 2004; Hsieh & Shannon, 2005) to identify the common themes in clinician responses to MBC feedback and to evaluate therapist responses that diverged from the FIT model. Given the study's aim to evaluate the FIT model, qualitative coding focused on four questions within the exit interviews (See Table 2) that included multiple choice responses inquiring about clinicians' feelings about using the PHQ-9 and their responses to PHQ-9 scores showing progress, no progress, or clinical deterioration.

In the first step of the coding process, a coding team consisting of the study PI, a Ph.D. level qualitative coding expert, and two research specialists independently reviewed two full exit interview transcripts to identify potential codes for inclusion in a coding dictionary. The coding team met weekly for approximately one month to come to consensus regarding common themes from the two transcripts, develop main code names, assign definitions to each main code, and compile the final coding dictionary. Given the focus on the four exit interview questions highlighted above, the main codes established reflected the responses to the four questions (see Table 2 for list of codes) The coding team then independently applied the established coding dictionary to two additional exit interview transcripts and met to discuss the coding process in order to ensure saturation of themes (i.e. that all FIT transcript content was able to be coded with established codes).

Table 2. FIT related exit interview questions and responses/main codes.

Question	Response Options/Main Codes
How do you feel overall about using the PHQ-9 in session?	A. Made a change to the treatment or session plan – How?*(change behavior)* B. Set new treatment goals better matched to your client – How?*(adjust standard of change)* C. Did nothing to change treatment because client is improving – Why? *(abandon standard of change)* D. Did nothing to change treatment because you felt the PHQ-9 was inaccurate – Why?*(reject feedback)* E. Other
When you received PHQ-9 scores showing your client was not making progress (*feedback sign: negative*), you typically:	A. Made a change to the treatment or session plan – How?*(change behavior)* B. Set new treatment goals better matched to your client – How?*(adjust standard of change)*

	C. Did nothing to change treatment because client is improving – Why? *(abandon standard of change)* D. Did nothing to change treatment because you felt the PHQ-9 was inaccurate – Why?*(reject feedback)* E. Other
When you received PHQ-9 scores showing your client was deteriorating (*feedback sign: negative*), you typically:	A. Made a change to the treatment or session plan – How?*(change behavior)* B. Set new treatment goals better matched to your client – How?*(adjust standard of change)* C. Did nothing to change treatment because client is improving – Why? *(abandon standard of change)* D. Did nothing to change treatment because you felt the PHQ-9 was inaccurate – Why?*(reject feedback)* E. Other
When you received PHQ-9 scores showing your client was making progress in treatment (*feedback sign: positive*), you typically:	A. Made a change to the treatment or session plan – How?*(change behavior)* B. Set new treatment goals better matched to your client – How?*(adjust standard of change)* C. Did nothing to change treatment because client is improving – Why? *(abandon standard of change)* *D.* Did nothing to change treatment because you felt the PHQ-9 was inaccurate – Why?*(reject feedback)* E. Other

Once the coding dictionary was established for the exit interviews, the study PI and two research specialists formally coded the 16 exit interviews using Atlas.ti software (Muhr, 1997). All three coders coded four transcripts, meeting weekly to establish inter-rater reliability through a reflexive team approach (i.e. reflecting on each code assigned and coming to consensus regarding coding disagreements). Once over 10% of the transcripts were coded by the full team including study PI with minimal reliability issues, the research specialist coders were cleared to independently code the remaining 12 transcripts. Inter-rater reliability meetings were held weekly with the study PI and research specialists, with the study PI providing oversight and knowledge of the coding dictionary to resolve coding disagreements within each of the transcripts coded.

Sub-coding procedure. Once all transcripts had been coded and inter-rater reliability was established for each of the 16 transcripts, the study PI and lead research specialist independently reviewed all clinician quotes coded with the FIT-relevant "Feelings about Using PHQ-9 in Session," "Response to PHQ-9 Scores Showing No Progress," "Response to PHQ-9 Scores Showing Deterioration," and "Response to PHQ-9 Scores Showing Progress" codes (see Table 2). This independent review process served two purposes: a) to identify common patterns of clinician behavioral approaches using FIT (i.e. changing behavior, changing goals, rejecting feedback due to inaccuracy, rejecting feedback due to client being unlikely to change, or other); and b) to identify potential sub-codes that would enable elaboration on how clinicians adjusted behavior in session as a result of receiving PHQ-9 feedback.

The study PI and lead research specialist met to discuss common themes and come to consensus on potential sub-codes to capture additional variation in clinician responses (i.e. codes within each of the FIT-relevant main codes above). For example, a sub-code of "adding additional treatment services" was added to identify a specific way that a clinician made changes to treatment in response to scores showing deterioration. Twenty-three sub-codes were identified through this reflexive consensus process (see Table 3 below for list of sub-codes).

Table 3. List of identified sub-codes for FIT behavioral responses to PHQ-9 feedback.

Clinician FIT Response	**Sub-code**
Change the therapy treatment plan (change behavior)	Clinician/client identification of session focus

	Client request for treatment plan changes Trying new treatment approaches Identification of client core problem/symptom Change treatment providers Increase/decrease session frequency Add treatment services
Make change to treatment goals (adjust standard of change)	New goals for symptoms not improving/high PHQ-9 score symptoms New goals missing from treatment plan New goals based on client preferences Set higher goals for symptom improvement Set goals for sustaining symptom improvement
Do nothing – client unlikely to change (reject standard of change)	Change unexpected early in treatment
Do nothing – PHQ-9 is inaccurate (reject feedback)	PHQ-9 inaccurate for client factors/diagnoses Client feelings that PHQ-9 is inaccurate
Other (not captured by FIT)	Tracking progress Identify barriers to change Review treatment goals Facilitate client engagement Enhance client symptom understanding Identify triggers Relate client symptoms to PHQ-9 scores Gather additional information

After sub-codes were identified, the study PI and lead research specialist completed a second round of coding in Atlas.ti software (Muhr, 1997) to assign sub-codes to the FIT-related main codes (see Table 2). The study PI and lead research specialist met to establish inter-rater reliability for all sub-codes assigned.

Qualitative Analysis Procedures

Queries were then run in Atlas.ti software (Muhr, 1997) to answer the following questions: a) what were the most frequently endorsed responses to FIT-related exit interview questions regarding how clinicians responded to feedback (questions 12-15; i.e. make a change based on feedback, reject the feedback and do nothing, reject the standard of change expected, or change the standard); b) to what degree do clinicians report changing treatment, adjusting goals, rejecting the standard, or changing the standard (i.e. alignment of clinician responses with FIT); and c) how do clinicians with "low," "medium," and "high" use of MBC differ with respect to their use of MBC in session.

Study 1 Results

Participants

Clinicians who participated in the exit interviews (N = 16) were 100% Female, 87.50% Caucasian, and had an average age of 39.25 years (SD = 11.41). All participating clinicians had Master's degrees, and approximately 69% were licensed mental health practitioners. The majority of clinicians identified Cognitive Behavioral Therapy as their primary theoretical orientation, and they reported a wide range of years of experience in mental health care provision (range from six months to 20 or more years). This sample of clinicians was generally representative of the larger population of clinicians across sites, as the majority of clinicians participating in the parent study are Female, Caucasian, and have Master's Degrees (see Study 2 Table 10). However, there was a higher percentage of Cognitive Behaviorally oriented clinicians in the exit interview sample when compared to the broad parent R01 clinician sample. See Table 4 for additional demographic information for participating exit interview clinicians.

Table 4. Demographic information for clinicians participating in exit interviews (N = 16).

Demographic Variable		Number of Clinicians (%)
Gender		
	Female	16 (100%)
Race		
	Caucasian	14 (87.50%)
	African American	1 (6.25%)
	Native American/Alaska Native	1 (6.25%)
Ethnicity		
	Non-Hispanic/Latino	16 (100%)

Highest Degree Obtained		
	Master's Degree	16 (100%)
Licensure Status		
	Currently Licensed	11 (68.75%)
	Not Licensed	5 (31.25%)
Theoretical Orientation		
	Interpersonal	1 (6.25%)
	Systems	1 (6.25%)
	Motivational Interviewing	2 (12.50%)
	Cognitive Behavioral	10 (62.5%)
	Other	2 (12.50%)
Years Experience		
	6-11 mos.	3 (18.75%)
	1-3 yrs.	3 (18.75%)
	3-5 yrs.	1 (6.25%)
	5-10 yrs.	3 (18.75%)
	10-20 yrs.	5 (31.25%)
	>20 yrs.	1 (6.25%)
Age		M= 39.25, SD = 11.41 Range = 24-60

Clinician Average MBC Adherence and Penetration

Participating clinicians were separated into low (N = 6), medium (N = 6), and high (N = 4) MBC use groups. Clinicians in the low group demonstrated infrequent use of MBC with their clients, with three of the six clinicians in the low group having zero adherence or penetration in the EHR across the 10 months post training. However, the low use clinicians who did have MBC data in the EHR used MBC in approximately five percent of their sessions. Medium use clinicians employed MBC in around 50% of their sessions, but reported that they typically did not review or discuss the PHQ-9 in session with clients (i.e. an average adherence score of "1" instead of "2" or "3." In contrast, the high use group used MBC in approximately 75% of their sessions, and reported higher PHQ-9 adherence scores suggesting more frequent PHQ-9 administration, review, and/or discussion in session.

Table 5. Average MBC adherence and penetration for low, medium, and high MBC use clinicians.

Clinicians	Average Percent Penetration (*SD*)	Average Adherence (*SD*)
Low (*N* = 6)	5.41% (8.24%)	0.05 (0.05)
Medium (*N* = 6)	51.22% (15.03%)	1.03 (0.31)
High (*N* = 4)	72.35% (3.07%)	1.55 (0.47)

Common Themes in Clinician MBC Behaviors

Negative feedback. When clinicians received MBC feedback that their clients were not progressing or were deteriorating in treatment (i.e. that the PHQ-9 scores were staying the same across sessions or becoming worse), they frequently endorsed gathering additional information from the client prior to choosing how to proceed with the PHQ-9 feedback (see Tables 6 and 7 for list of commonly endorsed responses). They specifically discussed having explicit conversations with clients to identify reasons for lack of progress. For example, some clinicians stated that, "Yeah, it might be other where I try to determine why that is not you know, what is going on that might be contributing to that [lack of progress]." Others noted:

> *"If I see that somebody is really floating around the same number [on the PHQ-9], we would talk about, maybe, barriers to change. Sometimes those barriers are, Well, I came here to work on post-traumatic stress, and my depression score isn't reflecting change, but my anxiety is reflecting change. We might say, Okay. Well, let's continue to give you the PHQ-9, but really we're going to crack down on this post-traumatic, and we'll see, as we've done treatments that are targeting the anxiety, how that reflects in your depression."*

Clinicians also most frequently endorsed making changes to the session or treatment plan (i.e. FIT change behavior response), especially as a result of receiving feedback that their clients were deteriorating. The most common change endorsed was trying new treatment approaches, such as incorporating sleep hygiene, elements of Cognitive Behavioral Therapy, or motivational interviewing into treatment. Clinicians also discussed changing the focus of the clinical session and working with the client to identify the core symptoms to be targeted in treatment. For example, clinicians reported using the PHQ-9 as a method for encouraging active engagement in treatment, noting that they would spend time in session discussing whether the client was willing to participate in therapy. They discussed that:

"Just use that [the PHQ-9] during session and see if we therefore need to make a treatment plan [change]. Just be sure they're on board. Kind of the idea of motivational interviewing. Don't make changes unless they're on board and also are motivated to address it."

Clinicians also endorsed treatment plan changes such as adding additional services (e.g. medication, substance abuse treatment), adjusting the frequency of sessions, and/or changing treatment providers. When responding to client lack of progress, one clinician stated, "…It might be where we might discuss incorporating medication or now wellness coaching so [treatment] could vary in that way." When responding to deterioration, another clinician noted that:

"If they're, let's say they went from a ten to a fifteen or a sixteen I want to know what's going on and look at some different facets. I don't think it's maybe one thing. Maybe they need to change providers. Maybe they [need] to see another therapist. Maybe they need EMDR. Maybe it's a co-occurring. Maybe they relapsed."

Table 6. Five most frequently endorsed clinician responses to MBC feedback showing no progress.

Theme (in order of frequency)	Exemplar Quote
Other – Gather Additional Information	"But I typically will discuss it with a client, and say, "Why do you think that this is showing your scores the same? Do you feel like you've made progress? If not, why not?"
Change Behavior – Try New Treatment Approaches in Session	"…I would, like, if they came in and they, especially if it was a safety question at the end of question number nine, like, they've had a lot of thoughts of harming themselves or not wanting to wake up, then I would definitely change the session to include safety planning."

Change Behavior – Clinician/Client Identification of Session Focus	“Maybe we just kind of slow down in some ways to do some symptom recognition which could be anger recognition or negative patterns of thinking or a common situation that keep triggering certain things.”
Change Behavior – Add Treatment Services	“Maybe it's adding case management. Maybe it's going from monthly to biweekly. Maybe it's going from biweekly to weekly. That's a hard one to say.”
Change Behavior – Client Directed Treatment Changes	“The whole treatment, yeah. So we might go back to medication, I might increase services, I might see them more frequently, do something a little different, ask them what they think might help.”

Table 7. Five most frequently endorsed clinician responses to MBC feedback showing deterioration.

Theme (in order of frequency)	Exemplar Quote
Other – Gather Additional Information	“Then I guess we would, in the session we would probably explore. Could there be something going on that's contributing, like a situational thing?”
Change Behavior – Try New Treatment Approaches in Session	“Yes. Maybe not the treatment plan, but the session plan. And again, that could be the answer to the previous question too. Just use that during session and see if we therefore need to make a treatment plan. Just be sure they're on board. Kind of the idea of motivational interviewing. Don't make changes unless they're on board and also are motivated to address it.”
Change Behavior – Clinician/Client Identification of Session Focus	*Interviewer:* “Yeah I think it's the second option. [Changing] What you're planning to do in the session.” *Clinician:* “ Yeah, then that one would make sense.”
Change Behavior – Add Treatment Services	“If they're regressing, getting severe, then I'm going to have to look into other avenues. I don't believe that the PHQ-9 is wrong, I think at that time that's how they're feeling. It just goes back to me again exploring and see where we're at and if there's any changes it has made in their

	lives. It's just, there again, addressing it and then if they're needing more services then I have to go further into their services. If it's me, if I'm the cause and I'm the reason why they're not making progress then I need to see if someone else can take on them, 'cause it's not about me it's about them. It's about trying to find what can help them."
Change Behavior – Client Directed Treatment Changes	"I guess it would depend on the score. If it was ... I think it would be up to the client as far as how they feel like they're doing and what they want to work on."

Positive feedback. Clinicians' responses to MBC feedback when clients were making progress in treatment significantly differed from responses discussed for lack of progress (see Table 8). Clinicians most frequently endorsed either doing nothing when they received feedback indicating progress (i.e. a FIT reject standard response) or setting higher goals or goals targeting remaining symptoms (i.e. a FIT adjust standard response). Clinicians noted ongoing monitoring and progress review with clients when they chose to reject the standard, stating that:

> *"If they're making the progress I'll leave things the way they are unless I see down the road where things are ... Where it's becoming ineffective, that either they've met these goals, or these goals aren't meeting all these needs, then I'll go over that."*

Clinicians also noted the potential for setting higher goals for their clients, setting goals to sustain change, or collaboratively identifying new goals with the client to target remaining clinically significant symptoms. They noted that:

> *"So I wouldn't do anything to change the treatment, but I'd look to see if there's a phase two or phase three of our treatment. Whether it'd be a higher goal or whether it'd be a gap in between sessions to test the sustainability of their changes. Or them being able to maintain it."*

Clinicians also reported that, "If it [symptom] was consistently improving then I would look towards either transitioning to new treatment goals because we had achieved previous ones." They also noted that they might consider reducing the frequency of sessions, highlighting that they might consider, "…even transitioning to decreasing services or whatever was most appropriate for that client."

Table 8. Five most frequently endorsed clinician responses to MBC feedback showing progress.

Theme (in order of frequency)	Exemplar Quote
Reject Standard – Do Nothing to Change Treatment	"If they're making the progress I'll leave things the way they are unless I see down the road where things are..."
Adjust Standard – Set Higher Goals for Changes in Treatment	*Clinician:* "…We'll see if it's consistent overtime, and then we make changes to the treatment goals." *Interviewer:* "So in that case you're adjusting the treatment so that they go for higher goals?" *Clinician:* "Mm-hmm (affirmative)"
Adjust Standard – Goal Setting Based on Client Preferences	"I think I would keep doing what we're doing. I might ask them if there's a change in goals they want to, that they've reached a good level and symptoms seem to be well in hand and kind of find out what they want to work on."
Change Behavior – Increase/Decrease Session Frequency	"Again depending on where they are, it might be a recommendation to have less frequent sessions for example."
Adjust Standard – New Goals for Symptoms Remaining/Not Improving	"I also think there's times when things get completely, you know, one issue that maybe was presented at one point is no longer an issue so we kind of shift to what else could be going on that maybe we can focus on to continue to enhance this person's quality of mental health and their life."

Alignment of Clinician MBC Behaviors with FIT

As highlighted above, the FIT identifies four behavioral responses that clinicians might engage in following receipt of MBC feedback on client progress. They may change their behavior and try new treatment approaches (change behavior), adjust the standard of change and set new goals for symptom improvement (adjust standard), reject the standard of change as their client is unlikely to change (reject standard), or reject the feedback due to believing that MBC with the PHQ-9 does not accurately assess client symptoms (reject feedback).

The majority of coded exit interview content aligned with the four FIT behavioral responses. Clinicians identified that they were most likely to change the treatment or session plan upon receiving feedback (changing behavior), followed by changing treatment goals (adjust standard). A few clinicians also reported that they would reject the standard of change and do nothing if they received feedback showing lack of progress or deterioration, especially early in treatment when change was unlikely to have occurred. Rejecting the standard of change was a more common response when clinicians received feedback showing progress, as many clinicians noted that they may not choose to make changes if the client demonstrated improvement. Very few clinicians reported that they would reject the feedback, highlighting reasons for rejecting including scores not reflecting client perception of symptom severity and the PHQ-9 not being accurate for certain comorbid diagnoses such as Obsessive Compulsive Disorder.

However, clinicians also identified several approaches to responding to feedback that did not fit neatly within the FIT model. In specific, clinicians frequently reported using the PHQ-9 to gather additional information, both from the client and from the treatment plan in order to identify reasons for symptom change. They noted that they would engage in this information gathering process prior to making a decision about how to use MBC in session. Additionally, clinicians reported using the PHQ-9 primarily to track progress, noting that progress or lack of progress does not necessarily require immediate decisions about making treatment changes. For example, clinicians noted that:

> *"That really depends on what kind of changes have been made, and what kind of progress has been made, and whether it's a sustained progress or a blip. So I might wait a couple of sessions [before making changes]."*

Differences Among Low, Medium, and High MBC Users

Changing behavior. Clinicians with low, medium, and high use of MBC demonstrated unique patterns of MBC in-session behavior. Although clinicians most frequently endorsed changing behavior in session as a result of negative feedback (i.e. when compared to the other FIT behavioral approaches), low and medium MBC users were more likely to change their behavior than high MBC users. Both low and medium MBC users endorsed trying new treatment approaches in session when noticing lack of treatment progress more frequently than high users. In fact, low and medium use clinicians were the only clinicians to endorse using the PHQ-9 as a tool to enhance client treatment engagement in session or to add treatment services.

Low users were also more likely than either high or medium users to report adjusting the frequency of sessions following receipt of negative MBC feedback. In comparison, medium MBC users were more likely to use MBC to encourage collaborative identification of what to focus on in session. Although high MBC users were less likely to report changing their behavior, those who did noted that they used MBC to guide the session focus in accordance with client preferences. There were no significant differences among low, medium, and high users regarding behavior change when they received positive feedback that the client was improving.

Adjust standard. There were very few differences among low, medium, and high use clinicians in their decisions to change treatment goals (i.e. adjusting the standard of change) as a result of receiving MBC feedback. Of those who did endorse changing goals, low use clinicians were the only clinicians to endorse that they would set higher goals or goals related to sustaining symptom improvement when they received feedback that their clients were improving (i.e. positive feedback). In contrast, both high and medium use clinicians were more likely than low use clinicians to discuss setting new goals in treatment based on client preferences or setting new goals for symptoms not yet been addressed when MBC scores indicated lack of progress or deterioration (i.e. negative feedback).

Reject standard. Medium use clinicians were more likely than low or high use clinicians to endorse rejecting the standard and not making changes in treatment when MBC indicated that the client was improving (i.e. positive feedback). Despite endorsing that they would continue with treatment as usual, medium use clinicians noted that they would engage in ongoing progress monitoring with the PHQ-9 to verify that changes to treatment were not needed. For example, they noted that:

> *"If they're making the progress I'll leave things the way they are unless I see down the road where things are ... Where it's [treatment's] becoming ineffective, that either they've met these goals, or these goals aren't meeting all these needs, then I'll go over that."*

Very few clinicians endorsed rejecting the standard of change because the client was unlikely to improve after receiving scores showing no progress or deterioration (i.e. negative feedback). Only one medium and one high use clinician noted that significant change may not occur early in treatment, stating that:

> *"...I wouldn't make any changes just because I'm kind of looking at ... It's been two weeks, this person may not change. If somebody's score continues to be consistently high and I*

really think they're making efforts, then certainly I would use that to look at the goals, look at what we're doing and see how we need to adjust treatment."

Reject feedback. Only three (two medium and one low use clinician) of the 16 participating clinicians reported instances of rejecting feedback due to believing that the PHQ-9 was inaccurate. The medium use clinicians reported that they might reject negative feedback due to the PHQ-9 being inaccurate for clients who reported consistently high scores across treatment or for clients with particular diagnoses not assessed by the PHQ-9, such as Asperger's or Obsessive Compulsive Disorder. The low use clinician reported that she may choose to reject negative feedback if the client feels the PHQ-9 does not show the client's true progress, stating that, "Sometimes the clients feel like that's [the PHQ-9's] pretty inaccurate, I have made progress." None of the clinicians reported that they would reject the feedback if they received positive feedback indicating client improvement.

Other. There were no differences among low, medium, and high use clinicians in using MBC to gather additional information about the reasons for symptom change prior to making treatment changes or in using MBC to track treatment progress over time.

Study 1 Discussion

Results from this qualitative study are the first, to our knowledge, to explore the utility of the FIT for capturing clinician approaches to using MBC in session. Outcomes of the clinician exit interviews largely supported initial hypotheses, as clinicians noted that their responses to receiving positive or negative feedback from the PHQ-9 commonly aligned with the FIT outcomes (i.e. changing behavior, adjusting standard, rejecting standard, or rejecting feedback). As expected, however, some clinicians did report diverging from the FIT in two key ways. For example, some clinicians noted that they would not engage in any of the responses after receiving negative feedback, instead using the PHQ-9 as an opportunity to either gather additional information about reasons for symptom change or to simply track progress without making treatment changes.

It is important to note that it may be quite challenging for community clinicians to identify how much depression symptom change should realistically occur in therapy (i.e. the standard of change). Clinicians in the community work with clients with high symptom severity and significant comorbid diagnoses, two predictors of low treatment response (Jarrett, Eaves, Grannemann, & Rush, 1991). Literature also suggests that community clients demonstrate slower rates of symptom change and higher rates of deterioration when compared to clients in managed care settings (Warren, Nelson, Mondragon, Baldwin, & Burlingame, 2010). Community clients may also present with substantial environmental stressors (e.g. poverty) that may have differential impacts on depressive symptoms from session to session (Harper et al., 2015). As a result, clinicians are charged with the task of gathering information about both the standard of change to expect from each of their clients and the potential for variation in this change due to weekly crises and ongoing stressors. These factors may explain clinicians' tendency to gather additional information from their clients prior to selecting one of the FIT behavioral responses, as changes may or may not be warranted depending on the consistency of clients' patterns of symptom change. Additional research is warranted to explore expected PHQ-9 standards of change in community mental health settings and the degree to which this standard is influenced by client factors.

It is also important to highlight that FIT is a theory guiding *individual* behavior change; therefore it may not be the optimal theory to capture both clinician and client behavioral responses to feedback. Given evidence suggesting that MBC is most effective when feedback is provided to both the clinician and the client, it is likely crucial to capture client responses to receiving feedback. Even clinicians' best efforts to make behavioral changes in treatment may be met with client resistance or low engagement, ultimately limiting the effectiveness of treatment (Westra & Dozois, 2006). In fact, a few clinicians noted in the exit interviews that they would need to have clients on board with changes prior to moving forward in treatment and that some of their clients felt the MBC feedback was inaccurate. Future research should focus on capturing both clinician and client responses to feedback, both to test the appropriateness of FIT for capturing the array of responses and to identify the impact of various clinician-client dyad feedback responses on depression symptom change.

There were also substantial differences in responses among “low,” “medium,” and “high” MBC users despite general alignment of responses with the FIT model. Most interesting was the outcome that low and medium clinicians were more likely to make changes to the treatment or session plan as a result of feedback showing lack of progress or clinical deterioration. One potential explanation for this finding is that low and medium use clinicians may be more likely to use MBC as a tool for guiding treatment changes more generally, while high use clinicians may strategically use MBC to make changes only with clients demonstrating lack of progress. Clinicians may also have over-reported their use of behavior change strategies, as the exit interviews required them to retrospectively report on their use of MBC and clinicians are vulnerable to over-reporting their use of EBPs (Brosan, Reynolds, & Moore, 2008; Pignotti & Thyer, 2012). Additional research is needed to explore differences in responses to feedback among clinicians with unique patterns of MBC use. Gaining additional insight into these differences may enable a better understanding of how much MBC is required to achieve symptom change as well as how varying MBC use levels feedback responses may interact to produce differential outcomes in psychotherapy for depression.

Limitations

Outcomes of this qualitative study have several limitations that should be noted. First, the interviews that were coded for this study took place 10 months after clinicians received initial MBC training. The exit interviews asked clinicians to self-report on their typical responses to MBC feedback without a specific timeframe or client in mind. This recall process may have resulted in biased or inaccurate responses, as clinicians may be thinking of different timeframes (i.e. MBC last week, last month, etc.) and often over-report their use and competence in evidence-based practices such as MBC (Brosan et al., 2008; Pignotti & Thyer, 2012). Second, three of the 16 clinicians who participated in the exit interviews did not have any adherence or penetration data pulled from the EHR and were therefore categorized as low use clinicians. However, all three clinicians indicated MBC use in their exit interviews, suggesting that the EHR data may not have captured the scope of their use with clients and the low use categorization may not have been appropriate. Third, as with most qualitative work, the sample size of this study was relatively small, and this qualitative analysis represents only 16 clinicians treating depression across six community mental health clinics. The responses of this limited sample size of clinicians may not generalize to community mental health clinicians more broadly.

Finally, it is important to note that as with all qualitative analyses, the data presented herein are prone to subjectivity and additional research may be needed using quantitative (i.e. clinician surveys) or mixed methods approaches to further evaluate the utility of the FIT. While a reflexive team analysis approach was employed to limit the subjective interpretation of clinician exit interview responses, the conversational interview data used in this study were vulnerable to the preconceptions and interpretations of the coding team. Despite these limitations, the qualitative design of this study allowed for a richer and more nuanced exploration of themes not generally possible with other data collection techniques, including the contextualization of findings using participants' own words.

Conclusions

In summary, clinicians generally employed MBC in session in line with FIT, suggesting that the FIT is valid for use in categorizing most behavioral responses to feedback in psychotherapy. Clinicians were most likely to change the treatment or session plan as a result of MBC showing lack of progress or deterioration. They were likely to continue with treatment as usual when MBC showed progress. However, clinicians also endorsed using MBC as an opportunity to gather additional information from their clients and track progress over several sessions prior to proceeding with treatment changes. This deviation from FIT highlights the complexities of deciding on a standard of symptom change and choosing how to proceed with complex community mental health clients. Results from this study have key implications for understanding clinicians' typical in-session responses to MBC feedback, prompting further exploration of the utility of the FIT model for MBC in psychotherapy for depression, and ultimately identifying additional putative mechanisms of change of MBC.

Chapter 2: Study 2 Introduction

Limited research has explored the degree to which clinicians choose to administer, review, and discuss MBC with clients in session, i.e. deliver MBC with fidelity. Psychotherapy fidelity assessment is frequently employed to ensure that EBPs are applied in session according to the guidelines that established them as evidence-based. Fidelity consists of three elements: treatment adherence, competence, and differentiation (Schoenwald et al., 2011). Adherence refers to the degree to which clinicians use an intervention like MBC as prescribed, while competence refers to the skill with which the clinician employs the intervention. Finally, differentiation refers to the degree to which an intervention can be identified as unique from other interventions (Schoenwald et al., 2011). Fidelity evaluation has become a key element of implementation studies that have sought to better understand the degree to which EBPs may be applied flexibly while maintaining their outcome enhancing effects (Kendall & Beidas, 2007). Given the complex nature of community mental health systems, many efforts to implement EBPs like MBC require substantial adaptation and tailoring to address contextual barriers and encourage use with fidelity.

There are numerous barriers to implementation that have been highlighted in the extant literature that may explain variability in clinician fidelity to MBC. These barriers often exist at both the organizational (i.e. clinic) and individual levels. At the organizational level, variable implementation of EBPs like MBC may be predicted by time limitations, low availability of resources, poor morale among staff, and norms among both leadership and clinicians that do not favor MBC use (Brunette et al., 2008; Pogoda, Cramer, Rosenheck, & Resnick, 2011). For example, specific barriers such as minimal availability of supervision, high productivity requirements, and short clinical sessions may limit perceptions of the utility of MBC, and may even prevent use completely (Scott & Lewis, *in prep*). In addition, low morale among staff has been linked to high turnover rates across mental health organizations, making it even more difficult to maintain a clinician workforce that is consistently trained and supervised in MBC application (Beidas et al., 2016; Glisson et al., 2008; McHugh & Barlow, 2010; Woltmann et al., 2008).

Many individual-level implementation barriers have also been established that predict variable MBC implementation. These individual-level barriers include clinicians' negative attitudes about MBC, perception of other clinicians' disapproval of novel practices, lack of knowledge, and need for individual training and supervision (Aarons, 2004; Aarons, Ehrhart, Farahnak, & Sklar, 2014; Beidas et al., 2015; Sadeghi-Bazargani, Tabrizi, & Azami-Aghdash, 2014). Community clinicians may also be especially vulnerable to concerns regarding the appropriateness of MBC given the complexity of their clients (Mitchell, 2011). For example, a few clinicians noted that they may reject the validity of MBC for clients with multiple diagnoses in Study 1 above. Finally, clinician training background and years of experience may also predict willingness to implement MBC. Previous literature suggests that clinicians with more years of experience may have received less training in EBPs, may have more negative attitudes, and may be less open to novel practices (Aarons, 2004; Beidas & Kendall, 2010; Stewart et al., 2012). Other studies also suggest that clinician age (Aarons, 2004; Beidas et al., 2015), gender (Beidas et al., 2015), and theoretical orientation (Nelson & Steele, 2007) may lead to more or less use of EBPs such as MBC.

As a result of these barriers, MBC application and fidelity in the community may vary significantly from the studies that established MBC as effective (see General Introduction). Even though it is a relatively less complex intervention than multifaceted treatments like Cognitive Behavioral Therapy (Beck, 2011), MBC has been variably applied across settings. Beyond the organizational and invidual barriers highlighted above, variation may also be due to the fact that MBC may take on unique formats, as it has been applied using electronic tools to help psychiatrists make decisions about medication management (Trivedi et al., 2007), using technology to enhance treatment in a community substance abuse clinic (Crits-Christoph et al., 2012), and using paper-and-pencil self report measures to enhance depression care in community behavioral health clinics (Lewis et al., 2015).

Despite documentation of variable MBC application, no efforts to our knowledge have characterized patterns of use and the degree to which these patterns map on to MBC adherence recommendations established in the literature. It is important to not only understand the degree to which clinician patterns of adherence deviate from recommendations established by the field (i.e. administering a measure, reviewing the score trajectory, and discussing with client at every session) but also to identify the characteristics of community clinicians with distinct patterns of MBC use. Gaining a better understanding of these characteristics may enable the identification of clinicians with high likelihood of MBC implementation who may be leveraged as champions and change agents within community mental health settings (Kitson, Harvey, & McCormack, 1998). In addition, understanding the impact of different patterns of MBC adherence on depression symptoms may enable the identification of the dosage of MBC required to maximize symptom change.

Evaluating MBC Adherence Patterns

Although variability in MBC adherence has been reported in the literature using retrospective clinician self-report or measures of implementation (Bickman et al., 2016; Connolly Gibbons et al., 2015; Whipple et al., 2003), it is possible that there are unexplored reliable and observable patterns of MBC use that can characterize subpopulations of clinicians over time. Single timepoint and variable-centered approaches to exploring how clinicians use MBC can be useful for characterizing adherence or identifying the degree to which MBC adherence is associated with positive outcomes. However, these variable centered approaches assume homogeneity among the population of clinicians employing MBC (Muthén & Muthén, 2000). As noted above, clinician characteristics may differentially impact MBC adherence, resulting in unique patterns of MBC use over time that may be missed through more traditional variable-centered approaches. Growth mixture modeling (GMM) is a person-centered analytic approach that allows for identification of unique subpopulations of individuals with common patterns of change over time (Jung & Wickrama, 2008; B. Muthén & Muthén, 2000; Wickrama, Lee, O'Neal,

& Lorenz, 2016). It is an approach that combines conventional growth modeling approaches with latent class analysis in order to identify classes of individuals, explore unique growth curves over time for each class, and estimate within class-variation through growth factor variances for each class (Muthén & Muthén, 2000). GMM also enables the exploration of predictors of class membership, thereby identifying the individuals who may be more or less likely to demonstrate a particular pattern of change. GMM may be especially well suited for identifying classes of clinicians who use MBC differently in community mental health settings.

GMM techniques have previously been employed in the literature to elucidate patterns of symptom presentation, symptom change over time, and predictors of these patterns in mental health treatment (Lutz, Stulz, & Köck, 2009; Yaroslavsky, Pettit, Lewinsohn, Seeley, & Roberts, 2013). GMM approaches have been employed to identify classes of individuals with high likelihood of substance dependence across their lifetimes (Muthén & Muthén, 2000), classifying individuals as normative drinkers, very heavy drinkers that decreased over time, heavy drinkers that decreased over time, and increased heavy drinkers over time. GMM approaches have also been explored to identify classes of individuals with unique response rates to depression medication (Muthén, Brown, Leuchter, & Hunter, 2008), to predict academic outcomes due to patterns in child caregiver sensitivity (Hirsh-Pasek & Burchinal, 2006), and to evaluate risk factors for poor school adjustment among homosexual youth (Murdock & Bolch, 2005).

For example, data from the Treatment for Adolescent Depression Study (TADS; Team, 2003) was subjected to GMM to identify three class of adolescents with unique symptom change trajectories: a high severity with early improvement class; a high severity with limited improvement class; and a moderate severity with late improvement class. The high severity with early improvement class was more likely to have high levels of baseline hopelessness and suicidal ideation when compared to other classes, providing crucial information that may guide identification of clients most likely to demonstrate early clinically significant change in psychotherapy (Scott, Lewis, & Marti, *under review*).

Despite GMM's power for evaluating unique individual patterns of symptom change and predictors of these patterns, GMM has been underutilized as a tool to evaluate clinician implementation of EBPs like MBC. A single study identified in the literature employed GMM for evaluating the impact of different levels of supervision for teachers on the implementation of a novel evidence-based teaching strategy in the classroom (Pas et al., 2015). Outcomes of the GMM identified three classes of teachers who received low, moderate, and high levels of support to employ an evidence-based teaching strategy. Teachers in the high and increasing support class demonstrated increased implementation of the teaching strategy, while low support teachers had the lowest implementation. Although these findings reflect patterns related to support received rather than EBP implementation, they highlight the potential utility of GMM for identifying relations among unique classes of individuals and EBP use.

The Present Study

In sum, GMM may be an important tool for identifying how clinicians use MBC, how different use patterns impact clinical outcomes, and which clinicians are most likely to implement MBC with adherence (i.e. predictors of class membership). The present study will serve to identify patterns and trajectories of clinician adherence and in-session MBC behaviors across treatment (Study 2 aim). Such procedures may provide insight into the the dosage of MBC needed to promote depression symptom change. The present study sought to leverage GMM to specifically identify patterns and trajectories of clinician adherence and in-session MBC behaviors across treatment, as well as predictors of these patterns and their impact on depression outcomes.

Hypotheses

It was anticipated that the GMM procedure would reveal three unobserved groups of clinicians with unique patterns of MBC use (**H1**). These three groups would be representative of high MBC adherence users, medium MBC adherence users, and low MBC adherence users. As discussed in Roger's theory on diffusion of innovations, the high MBC users would represent EBP early adopters who were experienced EBP users and therefore quick to accept and use MBC following training (Kitson et al., 1998; Rogers, 2010). In contrast, medium and low users would represent clinicians in the early/late majority and laggard groups, two groups taking longer to begin MBC implementation. Given the literature suggesting that diffusion of innovations occurs slowly over time with training and ongoing supervision of implementation (Rogers, 2010), it is anticipated that all three groups will demonstrate a slow increase in MBC adherence due to receipt of ongoing consultation or implementation team meetings across five months post training (Lewis et al., 2015). Some clinicians may also begin administering the PHQ-9 following training (adherence score of "1"), but may not review and discuss the PHQ-9 (adherence score of "3") until later in the five-month active implementation period while others may start with administering and reviewing and later increase to more frequent discussion (**H2**). Finally, it is also hypothesized that therapists who have fewer years of experience will be more likely to be members of the "high adherence" group (**H3**), given literature suggesting that individual-level barriers such as years of experience may impact MBC implementation (Aarons, 2004; Beidas & Kendall, 2010).

Study 2 Methods

Participants

All enrolled study clinicians in the parent R01 who provided at least one adherence observation during their five month active implementation period across the 10 sites were included in the analysis ($N = 92$). Given the dynamic cohort-based design of the study, clinicians from the different sites had unique timeframes for their active implementation (see Table 9).

Table 9. Timeline for 5-month active implementation for each site.

	Month 0 (month of training)	Month 1	Month 2	Month 3	Month 4	Month 5
Site 1 (C1)	7/2015	8/2015	9/2015	10/2015	11/2015	12/2015
Site 2 (C1)	7/2015	8/2015	9/2015	10/2015	11/2015	12/2015
Site 3 (C2)	12/2015	1/2016	2/2016	3/2016	4/2016	5/2016
Site 4 (C2)	12/2015	1/2016	2/2016	3/2016	4/2016	5/2016
Site 5 (C2)	12/2015	1/2016	2/2016	3/2016	4/2016	5/2016
Site 6 (C2)	1/2016	2/2016	3/2016	4/2016	5/2016	6/2016
Site 7 (C3)	5/2016	6/2016	7/2016	8/2016	9/2016	10/2016
Site 8 (C3)	5/2016	6/2016	7/2016	8/2016	9/2016	10/2016
Site 9 (C3)	5/2016	6/2016	7/2016	8/2016	9/2016	10/2016
Site 10 (C3)	5/2016	6/2016	7/2016	8/2016	9/2016	10/2016

Note. C1= Cohort 1, C2 = Cohort 2, C3 = Cohort 3.

Measures

Average clinician adherence. The primary measure for this study was average monthly therapist adherence to MBC measured across the five-month active implementation period (i.e. workshop training through five months post-training, see Table 9). This method was selected in order to obtain a measure of adherence at the clinician level, as the goal of the GMM analysis to be explored in the present study was to identify classes of clinicians. Client's session-by-session adherence scores ranging from "0" (i.e. no PHQ-9 completion) to "3" (i.e. PHQ-9 completion, review, and discussion in session) were pulled from the EHR. The average monthly adherence score for each clinician was then computed by taking the average of the adherence scores for each clinician across all of their depression pathway clients in a specific month (i.e. clinician adherence scores of 0, 2, and 3 in Month 3 would be averaged to obtain a Month 3 score of 1.67).

Covariates. Predictors of GMM class membership included clinician age, race, theoretical orientation, and years of experience providing mental health care. These covariates were considered as time invariant covariates as they were measured only at baseline for all clinicians. All of these predictor variables were selected given evidence suggesting their role in clinicians' openness and ability to implement novel EBPs like MBC (Beidas et al., 2015; Nakamura, Higa-McMillan, Okamura, & Shimabukuro, 2011; Nelson & Steele, 2007; Stewart et al., 2012). Race (white/non-white), theoretical orientation (Cognitive Behavioral/non-Cognitive Behavioral Orientation), and years of experience (less than five years/greater than five years) were included in the models as dichotomous variables, with a reference group of white for race, Cognitive Behavioral Orientation for theoretical orientation, and greater than five years for years experience.

Distal outcome variables. Average baseline and Month 5 PHQ-9 scores were also included in the analysis to identify whether class membership had an impact on client depression symptom change at the end of the active implementation period (i.e. Month 5). This method was again selected in order to have PHQ-9 symptom outcome data at the clinician level. To calculate average monthly clinician PHQ-9 scores, depression pathway clients' session-by-session PHQ-9 scores were first pulled from the EHR. This data was supplemented with baseline and Week 12 PHQ-9 scores collected for all enrolled clients by study research staff in order to maximize the data included in generating the average PHQ-9 scores. Average baseline PHQ-9 scores were computed two ways for the analysis: a) by taking the average PHQ-9 score of both new (i.e. clients who had started therapy after clinician MBC training) and ongoing depression pathway clients (i.e. clients who had started therapy prior to clinician MBC training) seen by a clinician during the month in which the clinician received MBC workshop training (i.e. Month 0); and b) by taking the average PHQ-9 scores for only new clients at Month 0. For example, if Client A had scores of 5 and 10 and Client B had a score of 20 during the month the clinician received MBC training, the clinician would receive an average client baseline PHQ-9 score of 11.67. Average Month 5 PHQ-

9 scores were also computed two ways by taking the average PHQ-9 scores of new and ongoing depression pathway clients seen by each clinician during the fifth month of active implementation as well as by taking the average PHQ-9 for only new clients.

Nesting variables and design effects. Given that clinicians were nested within sites, site was explored as a potential nesting variable to be accounted for in the analyses. Intra-class correlation values were computed to evaluate the impact of site on the variance in clinician adherence. Design effect scores were then calculated using the formula $DEFF = 1 + (n_c - 1)ICC$, where n_c is the average cluster size (i.e. average number of clinicians per site). Per the recommendations of Muthen & Satorra (1995), design effects greater than two were used to determine the need to account for nesting in all GMMs.

Growth Mixture Modeling Analyses

Average monthly adherence scores from the active implementation period (i.e. first five months post workshop training) were modeled using a four-step procedure with each step adding additional parameters, thereby increasing model complexity. Models were explored in the following order to identify classes of clinicians with unique trajectories of MBC adherence over time: a) basic growth model, b) Latent Class Growth Analysis (LCGA), c) Growth Mixture Model with class invariant variances and covariances (GMM-CI), and d) Growth Mixture Model with class variant variances and covariances (GMM-CV). This four-step procedure followed recommendations by Wickrama and colleagues (2016).

First, a basic growth model was fit to the data to identify the presence of changes in average clinician adherence over the five-month active implementation period. A quadratic term was then added to the model and the fit compared to the linear model to identify the optimal shape of the growth curve. Second, a series of Latent Class Growth Analyses (LCGA) were run to compare *k*

= 1 to k = 5 class models (i.e. models with total number of classes varying from 1 to 5) per recommendations from Wickrama et al. (2016). The LCGA is a restricted GMM model that enables the identification of unique mean intercepts and slopes across classes but fixes all within class variances to zero. Fixing the within class variances assumes that all trajectories of change are homogenous within each class and only estimates between class variances in growth factors (Berlin, Parra, & Williams, 2014). The LCGA approach is identified as a preferred second step in the model building procedure as it enables the identification of classes with lower computational burden than GMM (Wickrama et al., 2016).

Third, GMM-CI models were explored for k = 1 to k = 5 classes with invariant variances and covariances. The GMM-CI models allow for means and growth factors to be unique within classes, but holds residual variances and covariances of the growth factors equal across classes. Finally, GMM-CV models were explored for k = 1 to k = 5 classes to allow for the estimation of class variant variances and covariances.

All GMM models were fit using maximum likelihood estimation with robust standard errors in order to use all available data given the presence of missing data within the sample (Graham, 2009). The Bayes Information Criterion (BIC), entropy values, and average class probabilities were the primary criteria for determining the optimal number of latent classes of clinicians (Enders & Tofighi, 2008; Nylund, Asparouhov, & Muthén, 2007). The Bootstrap Likelihood Ratio Test (BLRT) could not be employed in this analysis due to inability to calculate BLRT values with nested, imputed data in Mplus statistical software. Per recommendations by Nylund and colleagues (2007), lower BIC values and higher entropy values identify better model fit. It is also optimal for all average class probabilities to be greater than 0.80, indicating a high probability of correct classification of individuals (Geiser, 2012).

After determining the appropriateness of GMM via the basic growth model, model fit indices for the LCGA, GMM-CI, and GMM-CV models with $k = 1$ to $k = 5$ classes were compared to identify models that minimized BIC, maximized entropy, and had average class probabilities above 0.80. Given the small sample size of clinicians being modeled ($N = 92$), the model selection procedure also sought to identify a model with classes with adequate prevalence (i.e. adequate number of clinicians in each class), as small class prevalence with a small sample size may not represent a true class (Dziak, Lanza, & Tan, 2014). Given the limited literature informing the selection of classes based on class prevalence, decisions regarding retention of classes with small membership were based on theory. For example, if fewer than 10% of clinicians fell into a class with a unique trajectory of adherence over time, the class was retained in the model to account for this unique variation. However, if the class membership was below 10% and the trajectory of change was not unique (i.e. similar slope estimates), the k-1 (i.e. the model with one less class) model was selected to maximize parsimony.

Three-Step Approach for Incorporating Predictors and Distal Outcomes

The three-step maximum likelihood (ML) approach for regressing latent classes on independent variables (i.e. predictors of class membership such as age and years experience) and distal outcomes (i.e. Month 5 PHQ-9 scores; Bakk, Tekle, & Vermunt, 2013; Vermunt, 2010) was then employed to explore differences across classes. The first step in the three-step approach involved identifying the best-fit model (see above). In the second step, a likely class membership variable was calculated from the best-fit model results. Third, two separate analyses were run to assess covariate predictors of class membership and differences between classes in baseline and Month 5 PHQ-9 symptom scores. The likely class membership variable (a categorical dependent variable) was first regressed on covariates (i.e. clinician age, gender, race, theoretical orientation, years of experience with therapy) using multiple logistic regression. Then, *Wald's Chi-squared* tests were assessed to test equality of mean baseline and Month 5 PHQ-9 scores among classes (Asparouhov & Muthén, 2013; Bakk et al., 2013). Overall, this three-step approach identified the number of different clinician groups (i.e. classes) with unique MBC adherence trajectories, assigned each clinician (N = 92) to a class, and explored whether predictor variables such as age and years experience and depression symptom outcomes differed among clinicians with unique patterns of MBC adherence.

Convergence Issues and Local Maxima

In order to minimize convergence issues and the presence of local maxima, common issues in GMM analyses with small sample sizes (Muthén et al., 2008), a high number of random starting values were used along with the OPTSEED procedure in Mplus to ensure the identification of global maxima and replication of the largest loglikelihood values across all models. (Wickrama et al., 2016). Random starts were selected based on the complexity of the model and ranged from 500 to 2000. After each model was run in Mplus, two additional OPTSEED runs were explored for each model using the two seed values with the best loglikelihood. This procedure was completed to ensure that parameter estimates were associated with the single largest loglikelihood value (i.e. the global maximum value) per recommendations from Wickrama and colleagues (2016).

Study 2 Results

Participants

The majority of clinicians (N = 92) were female (81.52%), Caucasian (83.70%), and non-Hispanic or Latino (97.83%). Most of the clinicians had Master's Degrees (91.30%), and more than half were currently licensed (60.87%) at the time of baseline data collection. Many also endorsed a primary theoretical orientation of Motivational Interviewing (48.91%), with others commonly identifying as eclectic therapists (18.48%). Clinicians were a wide range of ages (M = 44.34, SD = 12.59) and had a wide range of years of experience providing mental health treatment (66.30% with five or more years of experience).

Table 10. Demographic information for clinicians used in GMM analysis (N=92).

Demographic Variable		Number of Clinicians (%)
Gender		
	Female	75 (81.52%)
	Male	15 (16.30%)
	Missing	2 (2.17%)
Race		
	Caucasian	77 (83.70%)
	African American	9 (9.78%)
	Asian	1 (1.09%)
	Native American/Alaska Native	2 (2.17%)
	More than one race	1 (1.09%)
	Missing	2 (2.17%)
Ethnicity		
	Non-Hispanic/Latino	90 (97.83%)
	Missing	2 (2.17%)
Highest Degree Obtained		
	Bachelor's Degree	2 (2.17%)
	Master's Degree	84 (91.30%)
	Doctoral Degree	3 (3.26%)
	Other	1 (1.09%)
	Missing	2 (2.17%)
Licensure Status		
	Currently Licensed	56 (60.87%)
	Not Licensed	34 (36.96%)
Missing		2 (2.17%)
	Theoretical Orientation	
	Behavioral Modification	2 (2.17%)
	Integrative	5 (5.43%)
	Eclectic	17 (18.48%)
	Biological/Medical	5 (5.43%)
	Interpersonal	3 (3.26%)
	Systems	6 (6.52%)
	Motivational Interviewing	45 (48.91%)
	Cognitive Behavioral	2 (2.17%)
	Psychodynamic	2 (2.17%)
	Missing	5 (5.43%)
Years Experience		

	0-6 mos.	2 (2.17%)
	6-11 mos.	6 (6.52%)
	1-3 yrs.	17 (18.48%)
	3-5 yrs.	6 (6.52%)
	5-10 yrs.	17 (18.48%)
	10-20 yrs.	25 (27.17%)
	>20 yrs.	16 (17.39%)
	Missing	3 (3.26%)
Age		*M* = 44.34 (*SD* = 12.59, Range = 24-70)

Missing data – Monthly Adherence

Fifty-nine of the 151 clinicians enrolled in the parent R01 study had missing data for all monthly average adherence time-points (baseline to Month 5), resulting in a final sample of 92 clinicians with at least one observation across time points. Across time points, 29 adherence observations (31.5%) were missing at Month 0 (i.e. baseline), 15 (16.3%) at Month 1, 16 (17.4%) at Month 2, 13 (14.1%) at Month 3, 14 (15.2%) at Month 4, and 13 (14.1%) at Month 5. Monthly adherence data were fit using maximum likelihood estimation with robust standard errors to account for these missing observations and use all available data points, therefore imputation was not performed on these data (Graham, 2009).

Missing data – Predictors

For the clinician predictor variables, two out of 92 (2.17%) observations were missing for race, two for gender (2.17%), two for age (2.17%), five for theoretical orientation (5.43%), and three for years experience (3.26%). Multiple imputation was employed to account for all missing predictor values (see imputation procedure in General Methods section).

Missing Data – Distal Outcome

For the distal outcomes, 64 out of 92 (69.57%) observations were missing for average baseline PHQ-9 scores, while 44 observations were missing for average Month 5 PHQ-9 scores (47.83%). Multiple imputation was employed to account for missing distal outcome values, however the large percentage of missing data for both baseline and Month 5 average PHQ-9 scores was considered in interpretation of analyses.

Data Nesting

The study design involved the clustering of clients within sites, therefore site differences in adherence have the potential to contribute significant variability to the growth mixture modeling approach. An empty random intercept regression model was explored to determine the impact of site on adherence, identify the intra-class correlation values for all time points (i.e. percentage of variance in adherence accounted for by site), and test the need for clustering to be accounted for in all models. The random intercept model identified ICC's consistently above zero for all time points, suggesting a range of 12.1% to 33.9% of variance in clinician adherence is accounted for by site.

Table 11. Intra-class correlations for the random intercept regression model including site as nesting variable.

T0	0.150	T3	0.171
T1	0.139	T4	0.194
T2	0.339	T5	0.121

All design effect values were less than 2.0 except for T2 (i.e. average adherence in Month two post training). The design effect value for T2 suggests a need for multilevel modeling, as it is likely that ignoring the impact of nesting on the model will underestimate model standard errors. As a result, nested models will be explored accounting for the nesting of clinicians within site. However, given the small sample size of clinicians ($N = 92$) and the significant computation burden of multilevel modeling, the multilevel models had a number of convergence problems and limitations highlighted below.

Table 12. Design effect values for all time points to determine nesting.

T0	1.38	T3	1.57
T1	1.28	T4	1.78

T2	3.12	T5	1.11

Data Distribution

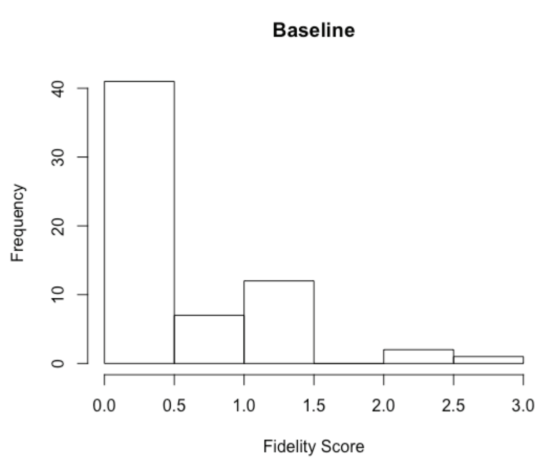
All monthly average adherence score values were highly skewed to the right (see Figure 1 for frequency distribution and Table 13 for skew statistics). All Kurtosis values were positive indicating that all monthly average adherence scores had heavy tails, also known as a leptokurtic distribution. These skew and kurtosis values suggest the presence of many “0” adherence values in the data set. Indeed, 34 (37.0%) adherence observations had a score of “0” for Month 0 (i.e. baseline), 44 (47.8%) for Month 1, 28 (30.4%) for Month 2, 25 (27.2%) for Month 3, 29 (31.5%) for Month 4, and 27 (29.3%) for Month 5.

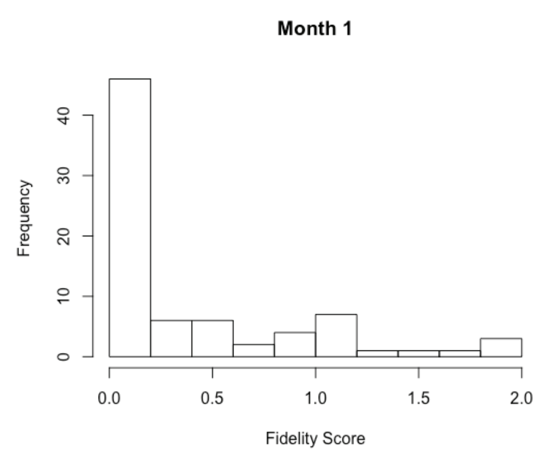
Table 13. Skewness statistics for monthly average adherence scores.

Month 0	1.69	Month 3	0.74
Month 1	1.55	Month 4	0.94
Month 2	1.44	Month 5	1.33

Table 14. Kurtosis statistics for monthly average adherence scores.

Month 0	5.56	Month 3	2.53
Month 1	4.57	Month 4	3.05
Month 2	4.32	Month 5	4.22





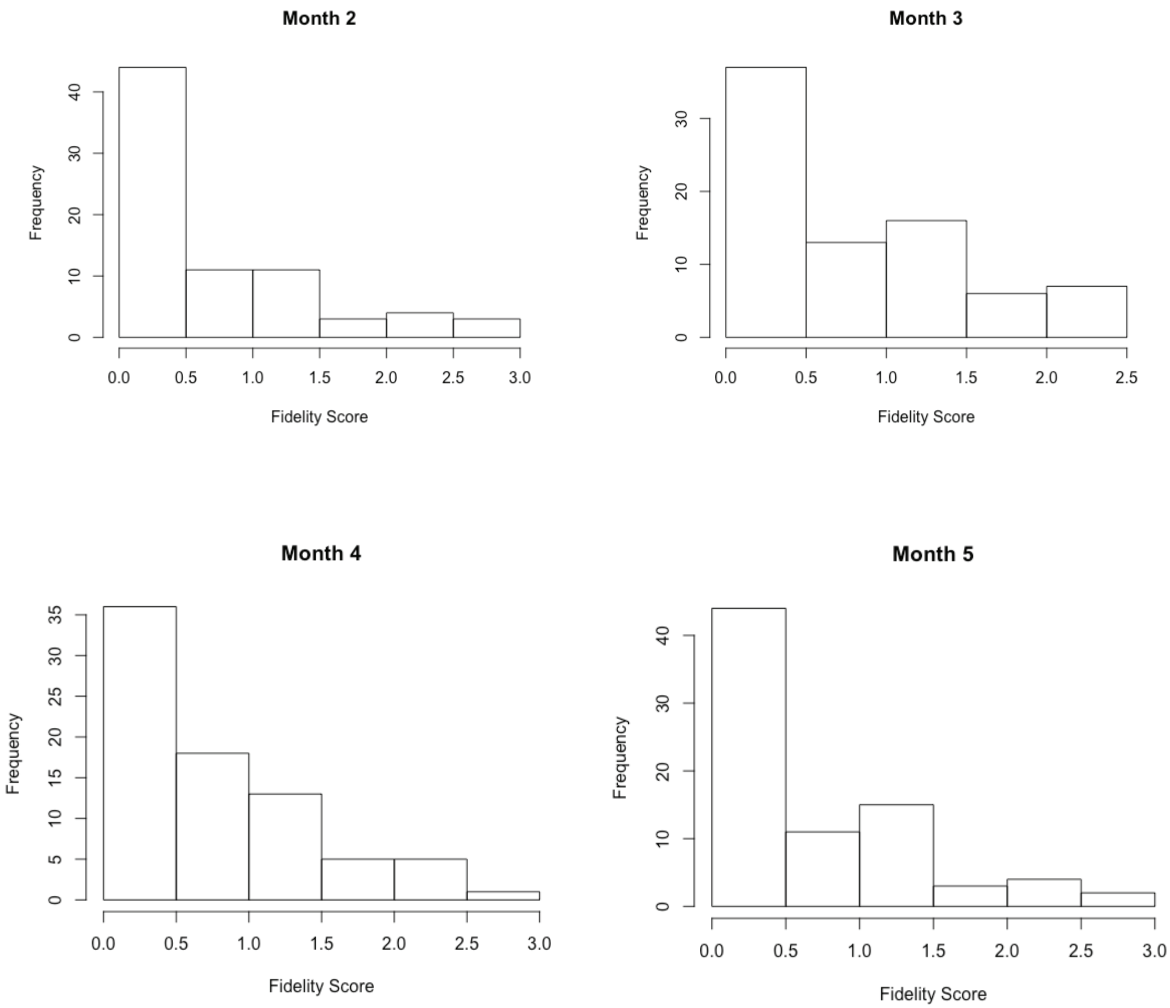


Figure 1. Histograms of distributions of average monthly adherence scores for clinicians.

Average MBC Adherence Over Time

Average clinician MBC adherence scores were quite low and ranged from 0.41 at baseline to 0.61 at Month 5 (see Table 15 below). However, standard deviation values suggest variability in monthly MBC adherence, therefore person-centered analyses were appropriate to identify patterns of MBC adherence that differ among clinicians.

Table 15. Average clinician MBC adherence scores for all clinicians (*N*=92) across five months post training.

Month	Mean (SD)
0 (baseline)	0.41 (0.63)

1	0.35 (0.53)
2	0.57 (0.74)
3	0.68 (0.69)
4	0.63 (0.67)
5	0.61 (0.71)

Correlations – PHQ-9 Adherence and Distal Outcomes

Correlations were explored among baseline PHQ-9 scores, Month 5 PHQ-9 scores, and average monthly PHQ-9 adherence across five months. Average monthly PHQ-9 were highly correlated (see Table 16). The correlations among baseline PHQ-9 scores and Months 2-5 PHQ-9 adherence trended toward (Months 2 and 5) or were correlated (Months 3 and 4). The correlation between Month 5 PHQ-9 scores and Month 0 PHQ-9 Adherence trended toward significance.

Table 16. Correlations among continuous variables of interest.

	BL PHQ9	M5 PHQ9	M0	M1	M2	M3	M4	M5
BL PHQ9	1.00	0.14†	0.02	-0.03	-0.18†	-0.26*	-0.28*	-0.18†
M5 PHQ9	-	1.00	0.19†	0.03	0.07	0.11	-0.09	0.17
M0	-	-	1.00	0.73**	0.46**	0.40**	0.20†	0.23*
M1	-	-	-	1.00	0.56**	0.49**	0.45**	0.45**
M2	-	-	-	-	1.00	0.63**	0.47**	0.40**
M3	-	-	-	-	-	1.00	0.73**	0.61**
M4	-	-	-	-	-	-	1.00	0.79**
M5	-	-	-	-	-	-	-	1.00

Note. † $p > 0.05$ but < 0.10; *$p<0.05$; **$p<0.001$.

Step 1: Linear and Quadratic Latent Growth Curve Modeling

The data were first subjected to a basic linear growth curve model (LGCM) to evaluate a linear trajectory of change over the five-month active implementation period.

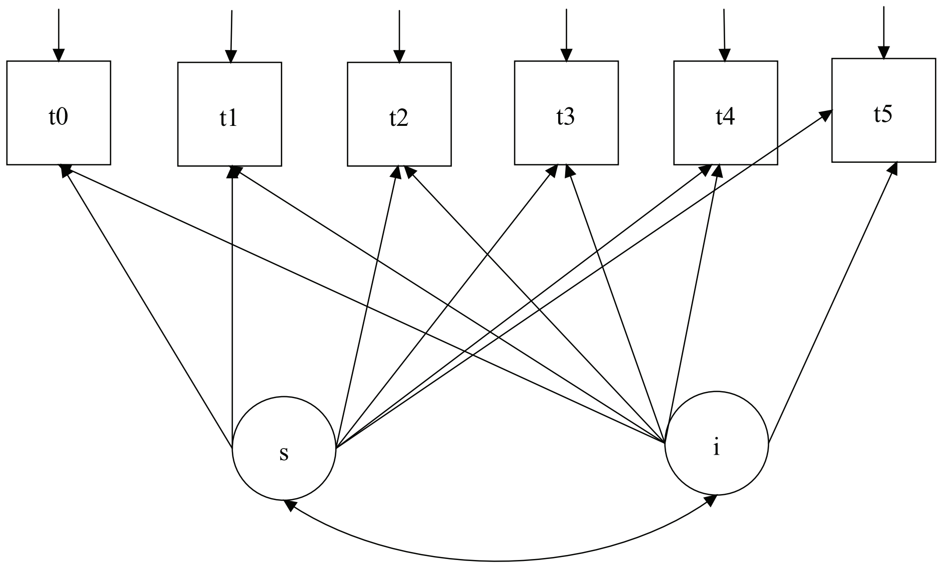


Figure 2. Basic LGCM model. t0 to t5 indicate observed average monthly clinician adherence scores, i and s represent latent intercept and slope variables to be estimated.

Unstandardized average estimates for the intercept ($I = 0.37$, $p < 0.0001$) and slope ($S = 0.06$, $p < 0.001$) suggested that the mean trajectory of adherence scores demonstrated an increase over time. Slope and intercept variances were also statistically significant (0.27, $p < 0.0001$ and 0.02, $p < 0.0001$, respectively), implying that some clinicians had higher or lower intercept adherence values than others, and that clinicians demonstrated significant variability in their rate of adherence change over time. Finally, there was a negative covariance between the slope and intercept (-0.033, $p < 0.008$), implying that clinicians who started out with higher adherence scores were more likely to experience score decline over the five-month period. Model fit indices suggested a poor fit to the data given the RMSEA value greater than the recommended cutoff of 0.06 and *Chi-squared* test with $p < 0.01$ (BIC = 755.58; χ^2(df) = 33.84(16), $p < 0.01$; RMSEA(90%) = 0.110 (CI: 0.06, 0.16). Overall, these results suggest substantial individual variation in intercept and slope of change in adherence scores, indicating that GMM analysis would be appropriate to identify patterns in individual trajectories of change.

The adherence score data was then subjected to a LGCM model including a quadratic term in order to evaluate the potential for a non-linear trajectory of change in average adherence scores across months. Model fit indices for the quadratic model (BIC = 762.44; χ^2(df) = 24.62(12), $p <$ 0.05; RMSEA(90%) = 0.11 (CI: 0.04, 0.17) indicate less optimal fit than the linear LCGM indices (higher BIC value, χ^2_{diff} (4) = 8.83 exceeding 9.49 based on $p < 0.05$). As a result, the linear trajectory of change was deemed best fit for the adherence data.

Step 2: Clustered Latent Class Growth Analysis (LCGA)

The data were then subjected to a clustered latent class growth analysis (LCGA) to assess the presence of unique trajectories of change in PHQ-9 adherence over time while accounting for variation due to clinicians nested within sites.

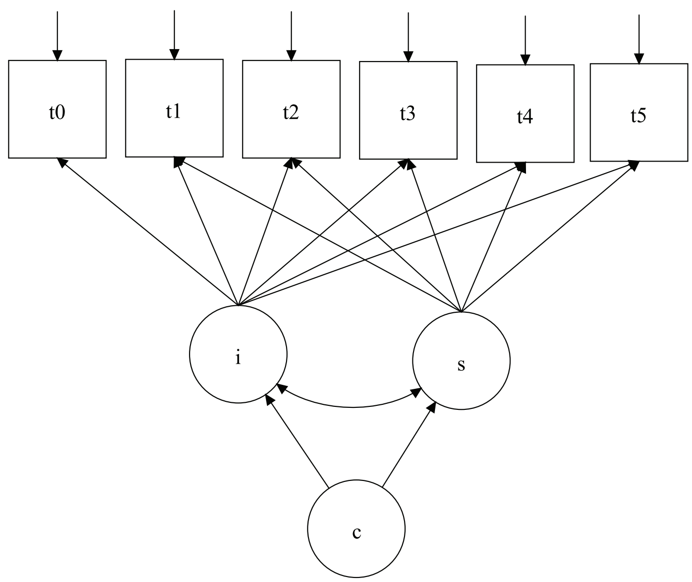


Figure 3. LCGA/GMM Model. t0 to t5 indicate observed average monthly clinician adherence scores, i and s represent latent intercept and slope variables to be estimated, c represents the latent class membership variable.

The LCGA approach was selected as an exploratory first step prior to engaging in GMM per the recommendations Jung and Wickrama (2008). LCGA models were fit with k = 1 to k = 5 classes (see Table 17 for fit statistics by number of classes). No convergence issues were identified.

LCGA model fit statistics. The LCGA models were compared on model fit statistics (see Table 17). Although the $k = 4$ and $k = 5$ models had the lowest BIC values, both models had classes with very small membership (i.e. classes with 4, 8, or 9 clinicians), suggesting that the classes may not be "true" or reliable classes given the small overall sample size. As a result, the $k = 4$ and $k = 5$ class models were not deemed to be the optimal fit for the data. The $k = 2$ model had the highest entropy value across all models as well as class membership representing substantial proportions of the data. However, the $k = 3$ model had a smaller BIC than the $k = 2$, suggesting the $k = 3$ model was a better fit model overall. In sum, the $k = 2$ or $k = 3$ models appear to be the best fit for consideration. The average latent class probabilities (Table 18 and 19) for both the $k = 2$ and $k = 3$ models enable the assessment of the adequacy of classification. Successful classification of clinicians into classes would result in high probabilities. Per recommendations from Geiser (2012), probabilities higher than 0.80 are considered adequate. Both the $k = 2$ and $k = 3$ models have adequate classification, as both have class probabilities greater than 0.90.

Table 17. LCGA model fit results.

Fit Statistics	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
LCGA					
LL (parameters)	-456.94 (8)	-378.27 (11)	-349.68 (14)	-333.52 (17)	-313.31 (20)
BIC	950.05	806.28	762.66	743.90	717.06
SSABIC	924.80	771.56	718.47	690.24	653.93
Entropy		0.929	0.878	0.898	0.880
Group Size (%)					
C1	92 (100.00%)	73 (79.35%)	48 (52.17%)	46 (50.00%)	47 (51.09%)
C2		19 (20.65%)	13 (14.13%)	9 (9.78%)	8 (8.70%)
C3			31 (33.70%)	33 (35.87%)	24 (26.09%)
C4				4 (4.35%)	4 (4.35%)
C5					9 (9.78%)

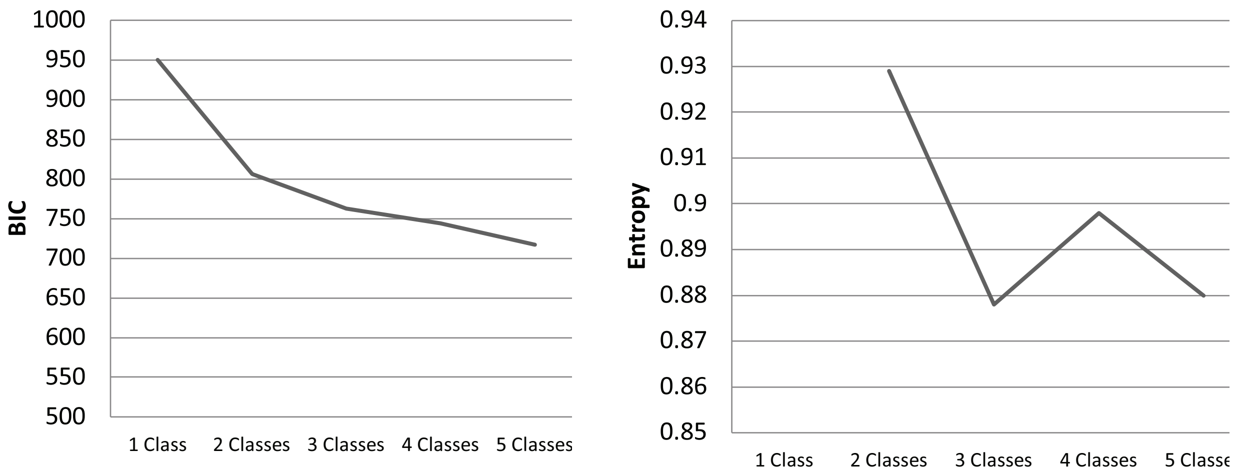


Figure 4. BIC and Entropy comparisons for unconditional LCGA models with different numbers of classes.

Table 18. LCGA k = 2 Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

	Class 1	Class 2
Class 1	0.962	0.038
Class 2	0.011	0.989

Table 19. LCGA k = 3 Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

	Class 1	Class 2	Class 3
Class 1	0.942	0.001	0.038
Class 2	0.011	0.922	0.057
Class 3	0.058	0.002	0.940

LGCA class trajectories. Initial exploration of the k = 2 model trajectories (see Figure 5) indicate two groups with similar slopes of change. Class 1 (N = 19) represents a minority of clinicians who appear to have completed the PHQ-9 (averaging a score of “1” on adherence) at Month 0 and then continued consistent use over time (the “High and Maintaining” Class). The change in Class 1’s adherence over time suggests that clinicians in Class 1 occasionally administered the PHQ-9 but did not often review scores or discuss with their clients. Class 2, with the largest number of clinicians (N = 73), began with fairly low adherence scores at Month 0 (immediately post training), and then demonstrated a slight increase in adherence over time (the "Low with Improvement" Class). However, average adherence values below one suggest that clinicians in Class 2 are reporting infrequent administration of the PHQ-9.

The $k = 3$ model trajectories indicate that the majority of clinicians were assigned to Class 1 and exhibited low PHQ-9 adherence at Month 0 and stayed low over time (the "Low and Maintaining" Class, N=48). In contrast, approximately 15% of clinicians were assigned to Class 2, a class that began with high PHQ-9 adherence and demonstrated an increase in adherence over time (the "High with Improvement" Class, $N = 13$). Finally, Class 3 represented approximately 35% of clinicians who started low in their adherence to MBC and experienced an increase in adherence over the five months following training (the "Low with Improvement" Class, $N = 31$).

Table 20. Intercept and linear slope estimates for $k = 2$ and $k = 3$ LCGA models.

	Intercept (*M*)	Standard Error	*p* value	Slope (*M*)	Standard Error	*p* value
k=2						
Class 1	1.094	0.231	0.000***	0.099	0.079	0.212
Class 2	0.152	0.057	0.008**	0.064	0.021	0.002**
k=3						
Class 1	0.220	0.095	0.020*	-0.021	0.031	0.500
Class 2	1.031	0.301	0.001**	0.202	0.077	0.009**
Class 3	0.380	0.198	0.054†	0.123	0.049	0.012*

Note. † $p > 0.05$ but < 0.10; *$p < 0.05$; **$p<0.01$; ***$p<0.001$

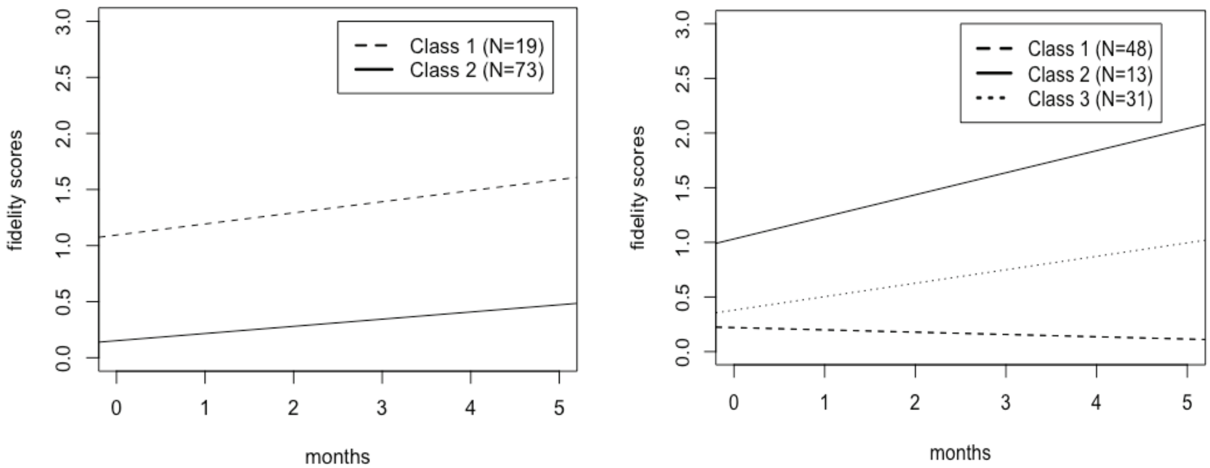


Figure 5. LGCA $k = 2$ and $k = 3$ model class trajectories.

LCGA summary. In summary, the exploratory LCGA models suggested that either a k = 2 (higher entropy) class or k = 3 class (lower BIC) model fit the data. Given that the k = 3 model provides the lowest BIC value, has class membership above 10% for all classes, and enables the identification of a unique class of clinicians who demonstrate decline in PHQ-9 adherence over time), the k = 3 model was deemed the optimal fit for further evaluation. The k = 3 model identified three separate classes of clinicians: a) Class 1 - “Low and Maintaining”; b) Class 2 – “High with Improvement”; and c) Class 3 – “Low with Improvement”. Further evaluation of the model is needed using GMM, as LCGA tends to overestimate the number of classes as it fails to model heterogeneity of individuals within classes (Wickrama et al., 2016).

Step 3: Clustered Three-Step Growth Mixture Modeling (GMM)

GMM models were then run assuming that all classes had equal variances and covariances (i.e. GMM-with class invariant variances and covariances/GMM-CI). Convergence issues were identified for the k = 5 GMM-CI model, suggesting over-extraction of classes.

GMM-CI model fit statistics. The k = 5 solution was discarded as it failed to replicate the maximum loglikelihood value. Although the $k = 4$ and $k = 3$ models had a slightly lower BIC values than the $k = 2$ model, both models had a class with only five percent to 10% of clinicians (see Table 21). This small class membership suggests that the classes may not be "true" classes, therefore providing evidence supporting the $k = 2$ model. The $k = 2$ model also had adequate average class probabilities, suggesting acceptable class classification. The $k = 2$ model was selected for further exploration. Compared to the LCGA models, all GMM-CI models demonstrated lower BIC values therefore suggesting that the GMM models are a better fit for the data.

Table 21. GMM-CI model fit statistics.

Fit Statistics	1 Class	2 Classes	3 Classes	4 Classes	5 Classes*
GMM - CI					
LL (parameters)	-351.91 (11)	-337.13 (14)	-318.82 (17)	-302.03 (20)	-297.52 (23)
BIC	753.56	737.57	714.50	694.50	699.03
SSABIC	718.84	693.37	660.84	631.37	626.43
Entropy		0.887	0.889	0.896	0.889
Group Size (%)					
C1	92 (100.00%)	17 (18.48%)	68 (73.91%)	62 (67.39%)	58 (63.04%)
C2		75 (81.52%)	17 (18.48%)	13 (14.13%)	12 (13.04%)
C3			7 (7.61%)	7 (7.61%)	7 (7.61%)
C4				10 (10.87%)	11 (11.96%)
C5					4 (4.35%)

Note. * = the model failed to replicate the maximum loglikelihood value with maximum number of starts, therefore estimates are untrustworthy and suggest over-extraction of classes.

Clustered GMM with class variant variances and covariances (GMM-CV). GMM-CV models were then run assuming all classes had unequal variances and covariances (i.e. GMM-with class variant variances and covariances/GMM-CV). GMM models were explored for $k = 1$ to $k = 5$ classes to enable comparison to the LCGA and GMM-CI results. Convergence issues were identified for the $k = 3$, $k = 4$, and $k = 5$ GMM-CV models, suggesting over-parameterization and over-extraction of classes.

GMM-CV model fit statistics and comparison to GMM-CI. The $k = 3$, $k = 4$, and $k = 5$ models were determined to be of poor fit for the data given low class membership in class two ($k = 3$ model) and convergence issues in the $k = 4$ and $k = 5$ models. The $k = 2$ GMM-CV with class variant variances and covariances was then compared to the $k = 2$ GMM-CI model with class invariant variances and covariances. The $k = 2$ GMM-CI model BIC (737.57) was lower than the $k = 2$ GMM-CV model BIC (753.88), suggesting an overall better fit for the GMM-CI $k = 2$ model. Per recommendations from Geiser (2012), classification probabilities higher than 0.80 are considered adequate. The $k = 2$ GMM-CI model also had adequate classification, as both classes had class membership probabilities greater than 0.90 (see Table 23). The GMM-CI model was selected as the final model for further exploration.

Table 22. GMM-CV model fit statistics.

Fit Statistics	2 Classes	3 Classes*	4 Classes**	5 Classes**
<u>GMM - CV</u>				
LL (parameters)	-338.51 (17)	-311.22 (23)	-304.98 (29)	-309.34 (35)
BIC	753.88	726.45	741.09	776.95
SSABIC	700.22	653.85	649.55	666.47
Entropy	0.930	0.835	0.821	0.896
Group Size (%)				
C1	11 (11.96%)	50 (54.35%)	0 (0.00%)	31 (33.70%)
C2	81 (88.04%)	9 (9.78%)	39 (42.39%)	54 (58.70%)
C3		33 (35.87%)	9 (9.78%)	0 (0.00%)
C4			44 (47.83%)	7 (7.61%)
C5				0 (0.00%)

Note. * = the model resulted in small class membership, suggesting the class may not be a true class; ** = the model failed to replicate the maximum loglikelihood value with maximum number of starts, therefore estimates are untrustworthy and suggest over-extraction of classes.

Table 23. GMM-CI $k = 2$ Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

	Class 1	Class 2
Class 1	0.939	0.061
Class 2	0.019	0.981

GMM-CI class trajectories The final selected $k = 2$ GMM-CI model identified two classes with unique intercept and slope values. Class 1 was identified as a "High and Maintaining" class, while Class 2 was identified as a "Low and Improving" class. These trajectories represent a departure from the LGCA results, as Class 1 clinicians no longer demonstrate an increase in PHQ-9 adherence over time, but instead largely maintain their level of adherence over time (slope p = 0.973). Class 2 demonstrated change over time ($p < 0.01$), with MBC adherence increasing across the five-month period.

Table 24. Intercept and linear slope estimates for the $k = 2$ GMM-CI.

	Intercept (M)	Standard Error	p	Slope (M)	Standard Error	p
Class 1	1.309	0.200	0.000***	-0.002	0.070	0.973
Class 2	0.124	0.056	0.027*	0.081	0.028	0.003**

Note. · trend toward significance; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

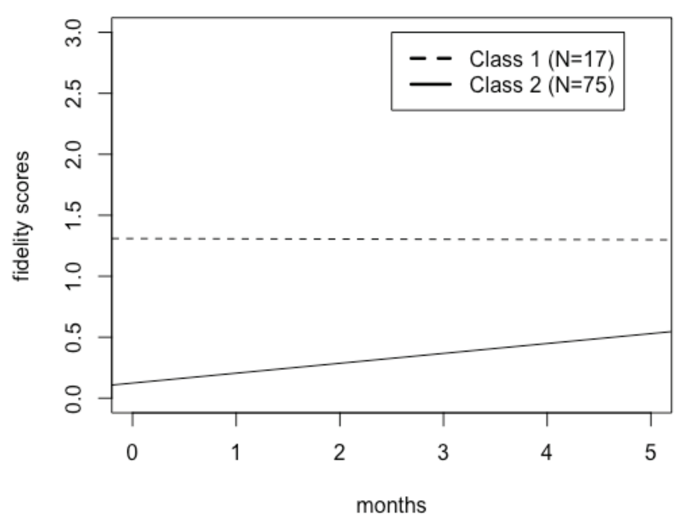


Figure 6. GMM-CI $k = 2$ model class trajectories.

Step 4: Predictors and Distal Outcome Differences Across GMM-CI Classes

GMM-CI Predictors. Age, race, gender, theoretical orientation, and years experience did not emerge as predictors of class membership in the GMM-CI $k = 2$ model (see Table 25).

Table 25. Multiple logistic regression predictors of GMM-CI class membership for $k = 2$ model.

Predictor	Class Contrast	Coefficient	*SE*	*t statistic*	*p*
Age	1 v. 2	-0.02	0.03	-0.81	0.42
Race	1 v. 2	2.50	4.38	0.57	0.57
Gender	1 v. 2	0.50	1.30	0.38	0.70
Theoretical Orientation	1 v. 2	0.38	0.29	1.32	0.19
Years Experience	1 v. 2	0.25	0.51	0.48	0.63

Note. Class 1 = High and Maintaining; Class 2 = Low and Improving.

GMM-CI Distal Outcome. There were no differences between classes with respect to mean baseline or Month 5 average PHQ-9 scores using Wald's *Chi*-squared tests for either all new and ongoing depression pathway clients (see Table 26) or for new clients only (see Table 27).

Table 26. Chi squared tests for mean differences in baseline and Month 5 PHQ-9 scores between classes in k=2 GMM-CI model.

Distal Outcome	Class 1 High and Maintaining *M* (*SD*)	Class 2 Low and Improving *M*(*SD*)	X^2	*p*
Baseline PHQ-9	13.93 (4.33)	12.60 (3.09)	1.73	0.19
Month 5 PHQ-9	10.95 (6.96)	12.72 (6.04)	0.62	0.43

Table 27. Chi squared tests for mean differences in baseline and Month 5 PHQ-9 scores between classes in k=2 GMM-CI model for new clients only.

Distal Outcome	Class 1 High and Maintaining *M* (*SD*)	Class 2 Low and Improving *M*(*SD*)	X^2	*p*
Baseline PHQ-9	15.10 (7.61)	15.20 (9.47)	0.002	0.96
Month 5 PHQ-9	13.012 (5.03)	11.86 (8.25)	0.382	0.54

Study 2 Discussion

This study was the first to our knowledge to apply GMM, a person-centered analytic approach, to quantitatively characterize patterns of clinician MBC use. Contrary to initial hypotheses anticipating three unique groups of clinicians, the two class GMM-CI model with class invariant variances and covariances was selected as the best fit model for the data (**H1**). This model identified two classes of clinicians with unique patterns of MBC adherence over time; one class that started with high adherence scores and maintained them (Class 1 - High and Maintaining) and one that started with low adherence scores and increased them (Class 2 - Low and Improving) over the five month active implementation period. Despite only supporting two unique groups, study results did support the presence of a class of clinicians starting with low adherence and slowly increasing over time. This finding partially supported study hypothesis two (**H2**), which predicted that clinicians would demonstrate an increase in adherence over the five month active implementation period in line with Roger's diffusion of innovations theory (Rogers, 2010). However, overall adherence was significantly lower than hypothesized, as average MBC adherence scores over time were often below or close to "1" (i.e. PHQ-9 administration only) across both classes of clinicians. Finally, study findings failed to support study hypothesis three (**H3**), as there were no differences between the two classes with respect to age, gender, race, theoretical orientation, or years of experience in mental health treatment. There were also no differences between classes with respect to depression symptom outcomes at Month 5 post training.

Although the findings did not support several of the hypotheses identified prior to analysis, the two class GMM-CI model did offer important insight into clinicians' approaches to integrating MBC into their clinical practice. The majority of clinicians (i.e. the "Low and Improving" class) appeared to be slow to begin use of MBC with adherence, but experienced a increase in adherence over time. This trend is perhaps not surprising, as clinicians should improve their use of MBC after receiving workshop training followed by ongoing consultation and supervision throughout the five-month active implementation period. Previous studies have highlighted the limitations of workshop training for promoting behavior change, therefore it is common practice to incorporate ongoing consultation into training approaches to encourage active learning and application of novel practices like MBC (Beidas & Kendall, 2010). Ongoing support provided in the parent study, either via consultation sessions focused on clinical questions or implementation teams focus on contextual and practical challenges, may have enabled clinicians in Class 2 to gain the skills needed and overcome barriers to enhance their adherence to MBC.

An alternative explanation for the “Low and Improving” class’s improvement over time may be improvement in their self-efficacy and control over using the PHQ-9 in session. As noted above, time and resource limitations are some of the most commonly identified barriers to using EBPs like MBC in community mental health settings (Baker et al., 2010; Jensen-Doss & Hawley, 2010; Lewis & Simons, 2011; Stewart et al., 2012). Clinicians often express beliefs that these barriers are outside their control and prevent their use of MBC because MBC requires additional time and they must comply with organizational policies that require large caseloads and high productivity requirements (Scott & Lewis, *in prep*). However, recent studies have suggested that clinicians may be able to overcome these challenges by achieving self-efficacy with EBPs like MBC (Shapiro et al., 2012), as MBC can actually streamline their work in session to focus on key problems. This increase in self-efficacy and efficiency using the PHQ-9 may then promote increased use of MBC over time (Scott, Wahlen, Lyon, & Lewis, *in prep*). Given that all clinicians had at least some MBC use immediately following training, it is possible that clinicians in the “Low and Improving” class experienced increases in MBC adherence over time due to enhanced feelings of self-efficacy upon successful application. Additional research is needed to evaluate the degree to which changes in MBC adherence over time may be due directly to enhanced clinician self-efficacy in MBC use, ongoing consultation and supervision, or a combination of both factors.

In contrast to the “Low and Improving” class, the “High and Maintaining” class captured a minority of clinicians who started off with higher adherence to MBC (i.e. scores indicating frequent administration of the PHQ-9) and maintained this adherence over the five month active implementation period. These clinicians may be early adopters of MBC, or individuals who have high interest in learning to use MBC and begin using it immediately after receiving training (McHugh & Barlow, 2010). Future research efforts might explore clinicians' use of MBC prior to training as a predictor of post-training use in order to discern between post-training early adopter clinicians and those who had been employing MBC prior to training. This approach may provide additional insights into patterns of clinician MBC use not identified in the present study.

It is surprising that some clinicians failed to improve their use of MBC over time despite ongoing support through consultation or implementation team meetings. Clinicians in the "High and Maintaining" class had average adherence scores between "1" and "1.5," suggesting they infrequently reviewed or discussed scores with clients across the five months post training. One possible explanation for both the "High and Maintaining" class's failure to improve their use of MBC as well as both classes' limited overall adherence to MBC (i.e. many adherence scores of "0", maximum around "1.5") is clinician's tendency toward selective use of MBC with only some of their clients. Despite receiving training focused on use of the PHQ-9 with all depressed clients regardless of client complexity (e.g. client diagnostic comorbidities, role functioning, crisis management), clinicians still reported selectivity in deciding with whom they would use the PHQ-9. As noted in Study 1 above, clinicians were hesitant to use the PHQ-9 with full adherence when clients were not engaged in treatment or when they had complex diagnoses.

These findings regarding clinician selective use of EBPs like MBC have also been reported in the research literature. Studies have identified high client comorbidity and client environmental chaos (Mitchell, 2011; Schoenwald, Halliday-Boykins, & Henggeler, 2003) as predictors of clinicians' limited use of EBPs. These findings may explain why average adherence to MBC was so low across both classes of clinicians in the present study (i.e. approximately 30% of scores reflected "0" adherence across all months), especially if the majority of clients seen by participating clinicians were quite complex. Future research is needed to identify client and clinician factors in this sample that limited MBC use and to explore methods beyond the training and consultation provided in the parent R01 study that may encourage clinicians to use MBC with even the most complex clients.

It is also important to note that the present study did not identify clinician characteristics that predicted class membership. These findings failed to replicate previous literature suggesting that gender, age, theoretical orientation, and years of experience may predict openness to and use of EBPs (Aarons, 2004; Beidas et al., 2015; Nelson & Steele, 2007; Stewart et al., 2012). It remains unclear what factors may contribute to whether clinicians fall into the "High and Maintaining" class or the "Low and Increasing" class. This study specifically explored individual clinician factors, such as years experience, race, and gender, which may not be the most influential variables in determining clinicians' patterns of MBC practice. However, more research is needed to explore additional organizational and individual-level predictors of class membership that may serve as barriers to EBP use such as attitudes toward MBC, clinician self-efficacy, and site organizational culture (Aarons, 2004; Aarons & Sawitzky, 2006; Jensen-Doss & Hawley, 2010).

Finally, class membership did not predict differences in clinical outcomes, a finding that is surprising given the strong evidence for MBC's effectiveness in enhancing depression outcomes (Lambert et al., 2001). However, the studies establishing MBC as effective provided clinicians with researcher-generated reports showing their clinicians progress, perhaps facilitating clinician review of client symptom scores. In the present study, clinicians had to manually enter PHQ-9 scores into the EHR and choose to review the trajectory, two additional steps that perhaps limited their review and discussion of scores. Additionally, although there is limited evidence regarding the necessary dose of MBC needed to promote change, Bickman and colleagues (2016) did note a dose-response relationship in their work using MBC with youth, with higher MBC adherence resulting in faster improvement. Other studies have also highlighted the importance of clinician and client discussion of feedback in order to maximize MBC's impact on symptom change (Lambert et al., 2001). It may therefore be the case that both classes of clinicians failed to apply the needed dose of MBC to promote change. More exploration of this potential dose-reponse relationship is warranted in order to identify the necessary dosage of MBC required to maximize symptom improvement.

Limitations

Several limitations should be noted regarding the study findings. First, outcomes from this GMM analysis study represent adherence patterns for MBC for depression across 10 sites within a specific community mental health organization. Recruitment for the parent R01 study is ongoing, therefore it is unclear how the results might change with the integration of the additional two sites (total of 12). It is also unclear the degree to which these findings might generalize to other diagnoses beyond depression or to other community mental health clinics and clinicians. Second, many clinicians opted not to use MBC with many of their clients, resulting in substantial frequencies of "0" scores for adherence as well as significant missing data and a small clinician sample size. This small sample size may have limited the ability to retain additional classes of clinicians who may have had unique trajectories of change in MBC adherence. Third, the need to have clinician-level indicators of adherence and depression symptom outcomes over time resulted in the computation of average monthly adherence and average baseline and Month 5 PHQ-9 scores for each clinician. Averaging the data in this way results in an inability to evaluate the variability of clinician MBC adherence and PHQ-9 scores within each time point, thereby reducing the number of observations as well as the potential to detect unique patterns of clinician adherence with individual clients. Additionally, average PHQ-9 score computations incorporated both new (i.e. clients just beginning therapy) and ongoing clients who may have been in various stages of symptom improvement at Month 5. As a result, the lack of findings regarding depression symptom outcomes may not be reliable due to significant variation in clients' amount of received therapy (i.e. ranging from a few sessions to months of treatment). Finally, there was substantial missing data for average clinician baseline and Month 5 PHQ-9 scores. Although these scores were imputed to enable comparisons across classes, estimates and group comparisons may not be trustworthy given the small sample of complete observations.

Conclusions

The findings from this study are the first attempt, to our knowledge, to identify unique patterns of change in clinicians' MBC adherence over time following workshop training. Results of the GMM analysis suggested that clinicians had two patterns of MBC adherence over time, high use that maintained and low use that increased. However, clinicians used MBC with full adherence quite infrequently, suggesting that clinicians failed to implement MBC with their depressed clients despite ongoing support from consultation and implementation teams during the active implementation period. These results may have important implications for identifying how much MBC is needed to promote depression symptom change, identifying clinicians who may benefit from targeted strategies to enhance adherence (e.g. additional training, supervision, evaluation of barriers), and ultimately for identifying MBC's core components and dosage of those components required to enhance depression outcomes for clients most in need.

Chapter 3: Study 3 Introduction

Although there is strong evidence supporting MBC's effectiveness, few studies have explored the putative mechanisms of change associated with MBC's impact on depression symptoms. The strongest evidence for how MBC works to produce symptom change currently comes from the psychopharmacology literature where MBC is typically used to inform decisions about antidepressant dosage and switching medications. Large randomized controlled trials such as the Sequenced Treatment Alternatives to Relieve Depression trial (STAR*D; Trivedi et al., 2006), Combining Medications to Enhance Depression Outcomes (CO-MED; Rush et al., 2011) and the Clinical Outcomes in Measurement Based Treatment trial (COMET; Yeung et al., 2012) suggest that MBC works by enabling the clinician to regularly evaluate symptom progress, make appropriate adjustments to medication dosages per recommended guidelines or an automated clinical decision support system, and ultimately see improved symptom outcomes (Morris & Trivedi, 2011; Trivedi et al., 2007). Additionally, use of MBC may enhance client adherence to medication regimens, perhaps as a result of frequent physician monitoring of dosages and side effects (Warden et al., 2014). MBC may also enable better collaborative stepped care among health providers, thereby enhancing the quality of both medication treatment and additional adjunctive care (Unützer & Park, 2012). In summary, MBC in psychopharmacology appears to operate by enabling clinicians to select the optimal dosages and dosage changes of psychiatric medication across treatment, thereby leading to improvements in outcomes for clients.

MBC's Putative Mechanisms of Action

Unfortunately, psychotherapy approaches to depression treatment often lack the specific guidelines present in pharmacology for when and how much to adjust the "dosage" of treatment. The variability in community clinician approaches to providing usual care psychotherapy makes identification of potential mechanisms of change quite difficult. However, correlational and qualitative studies of MBC applied in psychotherapy suggest several potential ways MBC may work to enhance outcomes in psychotherapy.

Symptom understanding. One putative mechanism of action of MBC in psychotherapy may be enhanced client symptom understanding resulting from completion of objective symptom measures prior to each clinical session. For example, Dowrick and colleagues (2009) found that clients who completed depressive symptom self-reports expressed that the measures allowed them to quantify and gain a better understanding of their depression symptoms. Additionally, Hall and colleagues (2014) reported that families felt the process of filling out the symptom measures was helpful for reflecting on progress and for being better prepared for each clinical session. MBC may also assist clients in their ability to better communicate their symptoms and experience in therapy to their clinician (Hall et al., 2014; Unsworth, Cowie, & Green, 2012; Wolpert, Curtis-Tyler, & Edbrooke-Childs, 2016).

Assessment accuracy. MBC may also produce change by enhancing clinician accuracy in their evaluation of client treatment progress and outcomes. It may also enhance clinicians' ability to quickly select interventions that are best suited to the client's symptoms. Strong evidence in the research literature suggests that clinicians have limited success gauging outcomes and predicting improvement by relying on clinical judgment alone (Grove, Zald, Lebow, Snitz, & Nelson, 2000; Jacinto, Lewis, Braga, & Scott, 2016). Instead, it is typically advisable for clinicians to rely on a combination of clinical experience and objective evaluation, such as by use of MBC and other reliable and valid assessments of progress (Jacinto et al., 2016; Sapyta, Riemer, & Bickman, 2005). MBC may function to enhance clinicians' objective evaluation of client progress, which may ultimately allow them to provide more effective therapy and enhance outcomes (Kelley & Bickman, 2009). It may also allow clinicians to more systematically identify risk, therefore enabling intervention prior to treatment failure or clinical deterioration (Lambert et al., 2005; Unsworth et al., 2012).

Intervention selection and tailoring. Additionally, clinicians may be able to more rapidly select interventions in between clinical sessions that would be an optimal fit for client symptoms, thereby enhancing the rate of change (Unsworth et al., 2012; Wolpert et al., 2016). They may also use MBC to "triage" clients based on their need for different dosages of therapy. For example, clinicians may use MBC to determine client severity, select an appropriate number of therapy sessions, and ultimately provide more tailored and effective treatment (Unsworth et al., 2012). Additionally, MBC may serve to identify the best clinician with the proper training to address client needs (Martin, Fishman, Baxter, & Ford, 2011). Clinicians may also use MBC to inform the specific questions asked in their own clinical supervision, thereby asking targeted questions and gaining better oversight of their most challenging clients (Lambert & Hawkins, 2001; Unsworth et al., 2012).

Treatment engagement. MBC may also operate by enhancing client treatment engagement. Treatment engagement has been defined in numerous ways in the psychotherapy literature, but is typically viewed as a client's emotional investment in treatment and willingness to make recommended behavioral changes (Lindsey et al., 2014). Treatment engagement is a multifaceted domain that has been measured by evaluating client treatment attendance/retention, participation in therapy sessions, and the clinician and client therapeutic alliance (Lindsey et al., 2014). Eisen and colleagues (2000) reported that the process of providing feedback (i.e. accessing treatment progress scores in session with the client) led to higher client reports of actively making decisions about treatment and feeling more engaged in the process of treatment when compared to clients who did not receive feedback in a quasi-experimental intervention trial. Other studies, specifically in substance abuse treatment, suggested that this enhanced perception of therapy involvement and improved communication with care providers resulted in higher treatment retention as well as enhanced clinical outcomes (Simpson, Joe, Rowan-Szal, & Greener, 1997, 1995). A recent meta-analysis specifically identified assessments, including MBC, as the most commonly employed approaches for encouraging client treatment engagement (Lindsey et al., 2014). These findings imply that enhanced treatment engagement may be an important mediator of the relation between MBC use and client outcomes and perhaps serve as a mechanism of change.

Treatment attendance has often been employed as a measure of client engagement as it may serve as an indicator of therapy "dosage" (Simpson et al., 1997, 1995). Poor treatment attendance is common in community mental health settings, with estimates suggesting that as many as 25% of community clients drop out of treatment prior to their first therapy session and as many as 35% drop out after the first therapy session (Simon et al., 2012). Even outside of community mental health, client rates of attrition from therapy range from 20% to 50% (Hatchett & Park, 2003; Swift & Greenberg, 2012). This poor attendance has been linked to reduced symptom improvement for clients (Cahill et al., 2003; Simpson et al., 1995), as well as reductions in morale and job satisfaction for clinicians providing treatment (Mensinger, Diamond, Kaminer, & Wintersteen, 2006).

An additional element of client treatment engagement is client willingness to engage in therapy skill practice both in and between sessions (i.e. therapy participation; Lindsey et al., 2014). Though not formally tested as a mechanism of change of MBC, enhanced client practice of therapy skills outside session upon seeing MBC progress may also explain MBC's effectiveness (Anker, Duncan, & Sparks, 2009). There are numerous elements that have been associated with client participation, including client commitment to therapy, willingness to spend time on therapy skills, and desire and perception of therapy's importance (Karver, Handelsman, Fields, & Bickman, 2005; Littell, Alexander, & Reynolds, 2001). However, few of these elements have been explicitly defined in the literature (Littell et al., 2001), and additional research is warranted to understand the variation in client participation and its potential impact on depression outcomes.

Finally, research in the couples intervention literature suggests that MBC may result in greater therapy engagement via an improved therapeutic alliance between clinician and client, thereby leading to enhanced treatment outcomes (Anker et al., 2009; Unsworth et al., 2012). Clients may also experience enhanced expectancies about their potential for change by seeing their current progress, which may simultaneously enhance the alliance and client improvement (Anker et al., 2009; Hall et al., 2014; Unsworth et al., 2012).

Moderated Mediation Techniques to Evaluate MBC's Mechanism of Action

Given the pragmatic nature of the parent R01 study and the challenges associated with treatment retention in community mental health settings, treatment engagement was identified as a putative MBC mechanism of change for further evaluation. Moderated mediation analysis is a novel approach to testing mediation effects that deviates from more traditional approaches as described by Baron and Kenny (1986). Baron and Kenny previously identified four key requirements for mediation analysis: a) variation in the independent variable must be associated with variation in the dependent variable; b) variation in the independent variable must be associated with variation in the proposed mediator; c) variation in the mediator must be associated with variation in the dependent variable; and d) when the independent and dependent variables are controlled for (with the mediator included), the relation between them is attenuated (Baron & Kenny, 1986). However, more recent work by Bollen (1989), Hayes (2013), and Preacher (2015) suggested that a lack of correlation between the independent and dependent variables (i.e. the direct effect) does not necessarily imply lack of causation, therefore mediation analysis can be conducted even in the absence of a direct effect.

Additionally, more modern approaches to mediation have explored mediation and moderation simultaneously. While unusual, this novel approach allows for the estimation of not only a mediating effect, but also the potential for the independent variable to moderate the relation between the mediator and the dependent variable (Hayes, 2013). In the case of treatment engagement as a mediator, MBC adherence could be explored as a potential moderator of the relation between engagement and depression symptom outcomes. If adherence does in fact moderate the relation, results would suggest that more adherence creates better quality sessions, thereby enhancing both client engagement in treatment and outcomes. This concept is supported in the EBP adherence literature, as good adherence is often a presumed prerequisite for delivery of EBPs with fidelity (Perepletchikova & Kazdin, 2005; Sharpless & Barber, 2009). In sum, this approach provides a novel way to evaluate whether client engagement serves as MBC's mechanism of action, as well as to assess the degree to which a higher MBC adherence may be vital for maximizing MBC's effectiveness.

The Present Study

In sum, a gap exists in the literature regarding the process and mechanisms by which MBC acts to produce change in depression symptom outcomes. Although it appears that providing feedback to both therapists and clients about client treatment progress is optimal (Lambert et al., 2005), more research is needed to explore how this feedback process operates to create change in depression symptoms. Prior evaluations of putative mechanisms of change for MBC have employed correlational approaches (Eisen et al., 2000), thereby limiting the ability to identify a causal relation between mechanisms of interest and improved symptoms. The present study will explore a formal simultaneous moderation and mediation analysis of one putative mechanism of change, treatment engagement measured by total client session attendance (Study 3 aim), in an effort to begin identifying MBC's key mechanisms of action.

Hypotheses

It was anticipated that increased client engagement in treatment via increased session attendance would mediate the relation between early session clinician MBC adherence (independent variable) and client symptom outcomes (dependent variable) such that higher clinician MBC adherence results in greater client treatment engagement, leading to improved outcomes (**H1**). Additionally, clinician MBC adherence would moderate the relation between treatment attendance and client outcomes, suggesting that enhanced adherence leads to enhanced effectiveness of the additional therapy sessions attended (**H2)**.

Study 3 Methods

Participants

Participants included clients who were enrolled in the study and who were just beginning psychotherapy (i.e. new clients) at one of the 10 sites (*N* = 88). These participants were drawn from a larger sample of 196 enrolled clients recruited into the parent study as of January 2017. Of the 196, only 109 clients were identified as new clients, while the remaining 87 clients were receiving ongoing therapy. An additional 21 clients were excluded from the analysis as they did not provide any adherence or session attendance data, resulting in a total sample of 88 clients for analysis.

Measures

Independent variable - adherence. Session one adherence scores and average session one and two adherence scores (independent variables for mediation modeling) were identified for each of the 88 enrolled clients included in the analysis. These adherence scores ranged from “0”, indicating no clinician MBC adherence, to “3”, indicating that the clinician administered, reviewed, and discussed the PHQ-9 with the client in the first session. An additional dichotomous adherence variable was also computed to identify clients who received at least some MBC at sessions one and/or two (i.e. a score of “1”, “2”, or “3”) or who received no MBC adherence (i.e. a score of “0”). These early session adherence scores were selected for the analysis as they were the earliest assessment of adherence prior to the client receiving the full “dose” of MBC across 12 weeks of treatment. Given that a substantial number of clients do not attend beyond the first therapy session (Simon et al., 2012), exploring session one and session two adherence may present a unique opportunity to evaluate a causal relation whereby early MBC adherence impacts client treatment engagement and results in clients coming back for more sessions. This approach using early session data has been explored in other studies as a method for evaluating putative mechanisms of action, as it is assumed that interventions at early sessions will precede changes in mediator and outcome variables (Karno, 2007).

Mediator variable – total sessions attended. The putative mediator variable, client treatment engagement, was measured by computing the total number of sessions attended across 12 weeks for all 88 clients included in the analysis. This 12-week period was selected as it is the standard acute phase of depression treatment in which clients are expected to achieve symptom change in clinical trials (March, Silva, & Vitiello, 2006). This 12-week period was also selected as the time frame for measuring symptoms given that many EBP approaches are brief in nature (e.g. 12 to 16 weeks).

Dependent variable – week 12 PHQ-9 scores. All 88 clients included in this analysis completed PHQ-9 measures as baseline and week 12 of treatment. Research specialists administered these PHQ-9 measures to clients over the phone. Week 12 PHQ-9 scores served as the primary dependent variable/outcome measure for this analysis, and all analyses controlled for baseline PHQ-9 scores in order to adjust for variability in client initial depression severity.

Covariates. The covariates selected for this analysis included client gender, race, and years of education. These three variables were selected as they have been explored as covariates in evaluating differences in depression symptom presentations and impact of interventions for depression. There are significant gender and racial differences in depression prevalence as well as symptom presentation (Barnes, Keyes, & Bates, 2013; Riolo, Nguyen, Greden, & King, 2005; Schuch, Roest, Nolen, Penninx, & de Jonge, 2014). Existing research has also demonstrated that higher years of client education are associated with fewer symptoms of depression (Ross & Mirowsky, 2006). Years of education also serves as one indicator of socioeconomic status, which has been established as a key indicator of risk for poor mental health (Braveman et al., 2005; Williams, Yu, Jackson, & Anderson, 1997). Gender (male/female) and race (white/non-white) were included in the models as dichotomous variables, with a reference group of males for gender and white for race. Years of education was included in the models as a continuous variable.

Data Nesting

Given that clients were nested within clinicians and clinicians within sites, both clinician and site were explored as potential nesting variables to be accounted for in the analyses. Intra-class correlation values were computed to evaluate the impact of site on the variance in clinician adherence. Design effect scores were then calculated using the formula $DEFF = 1 + (n_c - 1)ICC$, where n_c is the average cluster size (i.e. average number of clients per clinician Muthen & Satorra, 1995). Per the recommendations of Muthen & Satorra (1995), design effects greater than two were used to determine the need to account for nesting in the mediation analysis.

Mediation Analysis

All variables (independent, dependent, and mediator) were measured at the client level. Given this multi-level data, modeling procedures were employed in line with multilevel mediation recommendations from Lachowicz, Sterba, and Preacher (2015). The following relations were explored across three mediation models with unique independent variables: a) if there was an indirect effect of clinician MBC adherence (independent variable) via session attendance (mediator) on client outcomes (dependent variable); b) if there was a residual unmediated direct effect of clinician adherence on client depression symptom outcomes; and c) if clinician MBC adherence moderated the relation between session attendance and client symptom outcomes (see path diagrams in Figures 8, 9, and 10 below). Model one explored session one adherence alone as the independent variable, while model two explored average session one and session two adherence. Model three used a dichotomous adherence variable (i.e. if the client received any MBC adherence or not). All models were tested using multiple linear regression models (given continuous mediator and outcome variables) and were run in Mplus statistical software controlling for client baseline PHQ-9 scores, gender, race, and years of education.

Power Analysis

A power analysis was conducted prior to engaging in mediation analysis in order to determine whether the sample of 88 clients had adequate power (at least 0.80) to detect direct and indirect effects. A Monte Carlo simulation study was conducted per recommendations from Muthén & Muthén (2002), which involved the generation of 10,000 data sets, each with 88 clinicians clustered within sites of nine sizes (actual site sizes ranged from 1 to 26). All variables were simulated with means of zero and total variance of one. Mediation models were then run on these data sets, with all dependent variable residual variances fixed such that the total variance was equal to one (Thoemmes, MacKinnon, & Reiser, 2010). Given that previous literature did not exist to guide the expected magnitude of the relation among variables, estimates were included in the simulation to represent small (R^2 = 0.02), medium (R^2 = 0.13), and large effects sizes (R^2 = 0.26) for all paths (Cohen, 1988). All path estimates and residual variances were calculated using matrix algebra methods recommended by Thoemmes and colleagues (2010), Ma and Zeng (2014), and Fritz and MacKinnon (2007). The study sample of 88 was sufficient to detect direct and indirect path estimates with medium effect sizes. However, the study was not powered to detect small effect sizes, which may limit identification of significant, small but meaningful mediation.

Table 28. Power analysis for mediation models.

Path		Estimate	Power
Small Effect Size			
	a_1	0.126	0.288
	b_1	0.141	0.297
	c_1’	0.126	0.292
	a_1* b_1	0.018	0.022
Medium Effect Size			
	a_1	0.322	0.942
	b_1	0.361	0.967
	c_1’	0.322	0.970
	a_1* b_1	0.116	0.835
Large Effect Size			
	a_1	0.456	0.999
	b_1	0.510	1.00
	c_1’	0.456	1.00
	a_1* b_1	0.233	0.999

Note. a_1 = path from independent variable to mediator; b_1 = path from mediator to dependent variable; c_1’ = path from independent variable to dependent variable (direct effect); a_1* b_1 = indirect effect of the mediator.

Study 3 Results

Participants

Of the 88 clients used in the analysis, 63.64% were female, 79.55% Caucasian, and 5.68% Hispanic. Approximately 34.09% of clients were single and 36.36% were married. Sixty six percent of clients were not employed at the time of recruitment to the study, and 3.40% identified as students. Sixteen percent of clients had completed some high school, 34.09% had completed high school, and 29.55% had completed some college. The remaining 14.77% of clients had completed college or held advanced degrees (Associate's, Bachelor's, Master's, Medical Doctorate, Juris Doctorate, or Doctorate of Philosophy). See demographics and site distribution tables below (Table 29 and 30) for more information on participants.

Table 29. Study 3 client demographics (*N* = 88).

Demographic Variable		Number of Clients (%)
Gender		
	Female	56 (63.64%)
	Male	32 (36.36%)
Race		
	Caucasian	70 (79.55%)
	African American	14 (15.91%)
	Asian American/Pacific Islander	3 (3.41%)
	Native American/Alaskan Native	1 (1.14%)
Ethnicity		
	Hispanic/Latino	5 (5.68%)
	Not Hispanic/Latino	57 (64.77%)
	Missing	26 (29.55%)
Sexual Orientation		
	Heterosexual	79 (89.77%)
	Homosexual	6 (6.82%)
	Bisexual	1 (1.14%)
	Missing	2 (2.27%)
Relationship Status		
	Single and not dating	30 (34.09%)
	Dating	6 (6.82%)
	Cohabitating/living with partner	3 (3.41%)
	Engaged	4 (4.55%)
	Married	32 (36.36%)
	Separated	2 (2.27%)
	Divorced	11 (12.50%)
Education Level		
	Some high school	14 (15.91%)
	Completed high school/GED	30 (34.09%)
	Some college	26 (29.55%)
	Completed college	5 (5.68%)
	Advanced degree (M.A, J.D., M.D., Ph.D)	13 (14.77%)
Student Status		

	Student	3 (3.41%)
	Non-Student	84 (95.45%)
	Missing	1 (1.14%)
Employment Status		
	Employed	30 (34.09%)
	Unemployed	58 (65.91%)

Table 30. Study 3 client site distribution (N = 88).

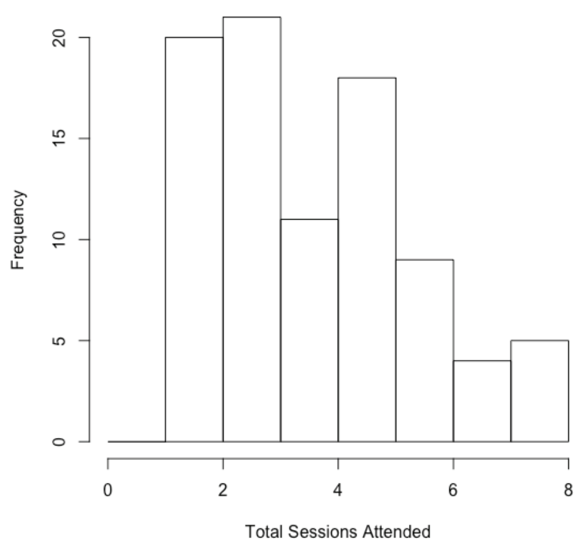
Site Number	Number of Clients (%)
1	13 (14.77%)
2	26 (29.55%)
3	6 (6.82%)
4	11 (12.50%)
5	10 (11.36%)
6	2 (2.27%)
7	1 (1.14%)
8	11 (12.50%)
9	3 (3.41%)
10	5 (5.68%)

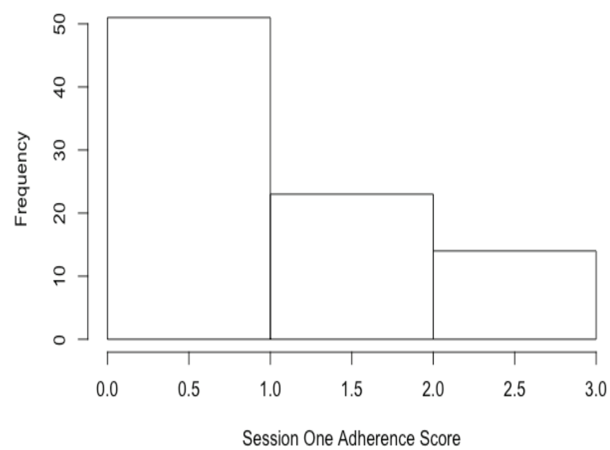
Missing Data

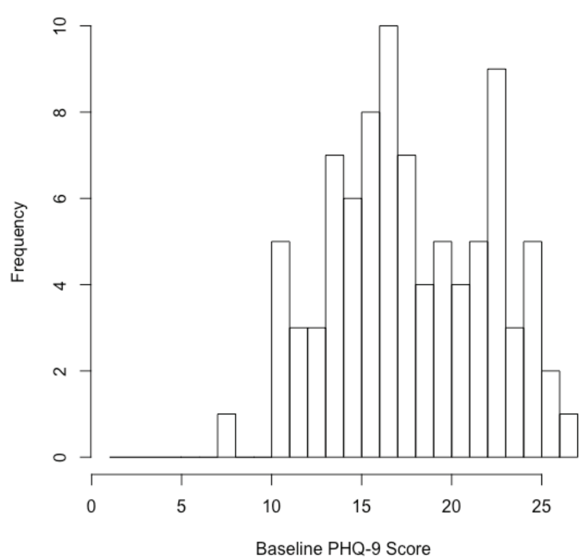
No missing data was present for total sessions attended, session one adherence scores, or baseline PHQ-9 scores as all enrolled, new clients provided baseline PHQ-9 data and clients without any adherence or session-by-session data were not included in the sample. Twenty-five clients (28.4%) did not provide week 12 PHQ-9 scores. Seventy-one clients (80.7%) did not have adherence data for session two, either because they failed to attend session two or because the clinician did not enter the PHQ-9 data into the EHR. No missing data was present for the control variables of interest (client gender, race, and education). The missing week 12 PHQ-9 scores were imputed using the procedures highlighted in the general methods section in order to avoid listwise deletion of cases.

Data Distribution

All variables of interest (Baseline PHQ-9 Score, Week 12 PHQ-9 Score, Session 1 Adherence Score, and total sessions attended) were positively skewed. It is of note that the session 1 adherence scores are skewed in the direction of “0”, suggesting infrequent use of the PHQ-9 at clients’ first therapy sessions.







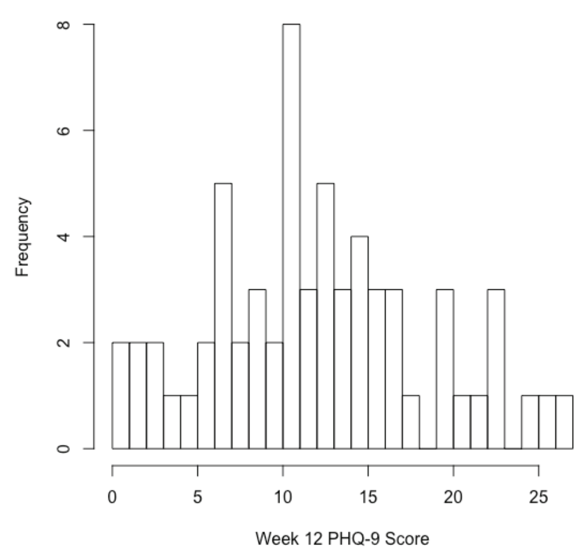


Figure 7. Distributions of total sessions attended, session one adherence scores, baseline PHQ-9 scores, and Week 12 PHQ-9 scores.

Table 31. Skewness statistics for continuous variables explored in mediation models.

Baseline PHQ-9	0.02
Week 12 PHQ-9	0.30
Total Sessions	0.77
S1 Adherence Score	1.32

Table 32. Kurtosis statistics for continuous variables of interest.

Baseline PHQ-9	2.17
Week 12 PHQ-9	2.65
Total Sessions	3.00
S1 Adherence Score	3.72

Descriptive Statistics – Client Depression Symptoms (PHQ-9 Scores)

Descriptive statistics were explored for client depressive symptoms measured with the PHQ-9. Clients (N = 88) reported clinically significant depressive symptoms at baseline (M = 17.28, SD = 4.36, Range = 7 - 26). The majority of clients (72.73%) endorsed moderately severe to severe symptoms according to PHQ-9 severity score cutoffs (see Table 33). However, week 12 PHQ-9 scores noted a reduction (see Table 34) in symptoms with a large effect size (M = 11.55, SD = 6.39, Range = 0 – 27, d = 1.05), with slightly over half of clients (51.15%) endorsing minimal to moderate depression symptoms after 12 weeks of treatment. It is important to note that there were no differences between those who did (i.e. an adherence score of at least "1") or did not (i.e. an adherence score of "0") receive MBC at session one with respect to baseline or week 12 depression symptoms, suggesting similar client depression severity levels regardless of MBC adherence. Both clients who received and did not receive MBC at session one demonstrated reductions in symptoms with large effect sizes (see Tables 35 and 36).

Table 33. Frequencies of PHQ-9 scores at baseline and week 12 for clients (N = 88).

Depression Severity	Baseline	Week 12

	N (%)	N (%)
Minimal Depression (PHQ-9 Score = 1 - 4)	0 (0.00%)	8 (9.09%)
Mild Depression (PHQ-9 Score = 5 - 9)	1 (1.14%)	14 (15.91%)
Moderate Depression (PHQ-9 Score = 10 - 14)	23 (26.14%)	23 (26.14%)
Moderately Severe (PHQ-9 Score = 15 - 19)	34 (38.64%)	10 (11.36%)
Severe Depression (PHQ-9 Score = 20 - 27)	30 (34.09%)	8 (9.09%)
Missing Data	0 (0.00%)	25 (28.41%)

Table 34. Mean differences across baseline and week 12 PHQ-9 scores for full sample of 88 clients.

	M (SD)	*t*	*p* value	Average Mean Difference	Cohen's *d*
Baseline PHQ-9 vs. Week 12 PHQ-9	17.28 (4.36) 11.55 (6.39)	7.24	0.000****	5.51	1.05

Note. ****p<0.0001.

Table 35. Mean differences in baseline and week 12 PHQ-9 severity for clients who did (score > 0, *N* = 37) or did not (score = 0, *N* = 51) receive MBC adherence.

	M (SD)	*t*	*p* value	Cohen's *d*
No Adherence Baseline PHQ-9	17.61 (4.43)	-0.83	0.41	0.18
Adherence Baseline PHQ-9	16.83 (4.29)			
No Adherence Week 12 PHQ-9	11.60 (5.71)	-0.06	0.95	0.02
Adherence Week 12 PHQ-9	11.50 (7.08)			

Table 36. Mean differences across treatment for clients who did (score > 0) or did not (score = 0) receive MBC adherence.

	M (SD)	*t*	*p* value	Average Mean Difference	Cohen's *d*
No Adherence (*N* = 51)					
Baseline PHQ-9 vs.	17.61 (4.43)	-5.73	0.000****	5.98	1.18
Week 12 PHQ-9	11.60 (5.71)				
Adherence (*N* = 37)					
Baseline PHQ-9 vs.	16.83 (4.29)	-4.52	0.000****	5.05	0.91
Week 12 PHQ-9	11.50 (7.08)				

Note. ****p<0.0001.

Descriptive Statistics – MBC Adherence and Total Sessions Attended

Clients attended an average of 3.11 total therapy sessions (*SD* = 1.85, Range = 1 – 8). At session one, clinicians' average MBC adherence scores were 0.66 (*SD* = 0.93, Range = 0 – 3). Clinicians' average session one and session two adherence scores remained comparable to session one with a mean of 0.68 (*SD* = 0.93, Range = 0 – 3). Fifty eight percent of clients did not receive any MBC at session one (i.e. an adherence score of "0"), therefore only 42% received any MBC (i.e. an adherence score of "1", "2", or "3"). This pattern remained consistent when looking at adherence scores across sessions one and two, as only 44.30% of clients received any MBC (see Table 38). Even when clinicians did use MBC in session, frequency counts of adherence scores suggest that very few clinicians reported viewing or discussing the PHQ-9 (i.e. scores of "2" or "3") in session one (see Table 39).

Table 37. Means and standard deviations for MBC adherence scores for early therapy sessions.

Variable Name	Mean(*SD*)
Total Sessions	3.11 (1.85)
S1 Adherence Score	0.66 (0.93)
S2 Adherence Score	0.71 (1.05)
Average S1/S2 Adherence Score	0.68 (0.93)

Table 38. Frequency counts for clients receiving no MBC (adherence score = 0) versus some MBC (adherence score > 1) across sessions one and two.

Variable Name	Frequency (%)
Adherence at S1	37 (42.00%)
No Adherence at S1	51 (58.00%)
Adherence at S1 or S2	39 (44.30%)
No Adherence at S1 or S2	49 (55.70%)

Table 39. Session one MBC adherence score frequencies.

Adherence Score		Frequency (%)
Session 1		
	0	52 (59.09%)
	1	23 (26.14%)
	2	7 (7.95%)
	3	7 (7.95%)

Session 2		
	0	10 (11.36%)
	1	4 (4.54%)
	2	1 (1.14%)
	3	2 (2.27%)
	NA	71 (80.68%)

Descriptive statistics were also calculated to identify the frequency with which clinicians were adhering to MBC across all sessions attended by clients (see Table 40). These percentages were computed by dividing the total number of sessions receiving an adherence score of "1", "2", or "3" by the total number of sessions attended by each client. For example, consider a client who attended five total sessions and the clinician administered PHQ-9's at the first three sessions (i.e. adherence score of "1"), administered and reviewed the scores at the fourth session (i.e. adherence score of "2"), and did not use the PHQ-9 at the fifth session. In this case the client would receive an overall PHQ-9 adherence percentage of 80% (adherence greater than "0" at four out of five sessions), an administration adherence percentage of 60%, an administration and review adherence percentage of 20% and an administration, review, and discussion percentage of 0%.

Table 40. Average percentage of attended sessions with adherence scores ranging from 0-3.

MBC Adherence	Average % of sessions attended
Adherence score > 0	46.59% (Range = 0% - 100%)
Adherence score = 1	28.39% (Range = 0% - 100%)
Adherence score = 2	8.55% (Range = 0% - 100%)
Adherence score = 3	9.93% (Range = 0% - 100%)

Descriptive Statistics – Correlations Among PHQ-9, Adherence, and Sessions Attended

Correlations were then explored among baseline PHQ-9 scores, week 12 PHQ-9 scores, session one adherence scores, average session one/session 2 adherence scores, and total sessions attended. Variables of interest did not correlate (see Table 41). However, the correlation between average session one and session two adherence and baseline PHQ-9 trended toward significance ($p = 0.097$).

Table 41. Correlations among continuous variables of interest.

	Baseline PHQ-9	Week 12 PHQ-9	Total Sessions	S1 Adherence Score	Average S1/S2 Adherence
Baseline PHQ-9	1.00	0.39**	-0.07	-0.17	-0.18†
Week 12 PHQ-9	-	1.00	0.03	-0.10	-0.13
Total Sessions	-	-	1.00	-0.03	-0.002
S1 Adherence Score	-	-	-	1.00	0.98**
S2 Adherence Score	-	-	-	-	1.00

Note. † p > 0.05 but < 0.10; *p<0.05; **p<0.001.

Evaluating Need for Model Nesting

Need for nesting within clinicians. Intra-class correlations (*ICCs*) were explored to determine the variances in the dependent, independent, and mediator variables to be explored (i.e. Week 12 PHQ-9 Scores, total number of sessions attended) due to clients being nested within clinicians. All 88 clients were nested within 39 clinicians, with an average of 2.26 clients per clinician (Range = 1 client to 7 clients per clinician). Week 12 PHQ-9 *ICC* was 0.056, baseline PHQ-9 was 0.114, total sessions attended was 0.215, and session one adherence score was 0.467. These *ICC* values corresponded to design effects of 1.07, 1.14, 1.27, and 1.59, respectively. Given that the design effects are less than two, recommendations from (Muthen & Satorra, 1995) suggest that the modeling procedures do not need to account for variance due to between clinician effects.

Need for nesting within sites. *ICC* values were then explored to determine the variances in the dependent, independent and mediator variables due to clients being nested within sites. The 88 clients were nested in one of 10 sites, with an average site size of 8.8 clients (Range = 1-26). The *ICC* value was 0.061 for baseline PHQ-9 score, 0.008 for week 12 PHQ-9 score, 0.136 for total sessions attended, and 0.23 for session one adherence score. Baseline PHQ-9, week 12 PHQ-9, and total sessions attended all had *ICC* values with design effects less than two (1.48, 1.06, and 1.98, respectively with $n_c = 8.8$). However, adherence score design effects were greater than two,

($DEFF$ = 2.79), suggesting that modeling procedures do need to account for variance due to between site effects.

Regression Models Accounting for Nesting

Simple regression models were then explored to identify additional predictors of week 12 PHQ-9 scores and total session attendance (two dependent variables to be explored in mediation analysis) in order to explore potential control variables for the mediation models. Each predictor was explored in a separate model and all models were two-level models accounting for nesting due to site. Baseline PHQ-9 score was the only predictor of week 12 PHQ-9 scores (B = 0.277, p = 0.007), with the result in the expected direction (i.e. higher baseline PHQ-9 predicted higher week 12 PHQ-9). Race was a predictor of total sessions attended (B = -1.553, p = 0.000). Compared to white clients, non-white clients attended 1.553 fewer clinical sessions on average. Gender (B = 0.664, p = 0.069) and years of school (B = 0.184, p = 0.095) trended toward being predictors of total sessions attended. Compared to male clients, female clients appeared to attend an average of 0.644 additional sessions. Additionally, higher years of schooling predicted higher session attendance such that a one unit increase in years of schooling led to an increase of 0.184 sessions attended on average. Baseline PHQ-9, gender, race, and years schooling were included as control variables in all mediation models explored below given the associations among these variables and the dependent variables of interest (week 12 PHQ-9 and total sessions attended).

Table 42. Two level simple regression models with each predictor included in a separate model.

Variable	B	*Standard Error*	t-statistic	p value	R^2	p value
DV = Week 12 PHQ-9						
Baseline PHQ-9	0.287	0.103	2.696	0.007**	0.078	0.180
Session 1 Adherence	-0.748	0.696	-1.074	0.283	0.015	0.500
Average S1/S2 Adherence	-0.943	0.591	-1.595	0.111	0.022	0.330

Session 1 Dichotomous Adherence	0.186	2.175	0.085	0.932	0.003	0.889
Total Sessions	0.026	1.940	0.014	0.989	0.002	0.969
Gender	-1.234	2.428	-0.508	0.611	0.012	0.740
Race	0.231	6.487	0.036	0.972	0.000	0.977
Years of School	-0.183	0.360	-0.509	0.611	0.004	0.796
DV = Total Sessions						
Session 1 Adherence	0.020	0.178	0.110	0.912	0.000	0.956
Average S1/S2 Adherence	0.077	0.166	0.464	0.643	0.002	0.813
Session 1 Dichotomous Adherence	0.225	0.338	0.665	0.506	0.004	0.734
Gender	0.664	0.365	1.819	0.069†	0.034	0.337
Race	-1.553	0.230	-6.763	0.000***	0.035	0.000***
Years of School	0.184	0.110	1.669	0.095†	0.048	0.365

Note. † $p > 0.05$ but < 0.10; **$p < 0.01$; ***$p < 0.001$.

Moderated Mediation Model 1 – Session 1 Adherence

A moderated mediation model was then fit to evaluate path estimates controlling for baseline PHQ-9, gender, race, and years of school. The first model explored was a moderated mediation model with an independent variable of session one adherence, a mediator variable of total sessions attended, and a dependent variable of week 12 PHQ-9 score. Session one adherence was also evaluated as a moderator of the relation between total sessions and week 12 PHQ-9 to determine if zero (score of "0"), moderate (score of "1"), or high levels (score of "2" or "3") of MBC adherence had a differential impact on the effectiveness of sessions attended for reducing depression symptoms. See Figure 8 below for an overview of the model and paths to be estimated.

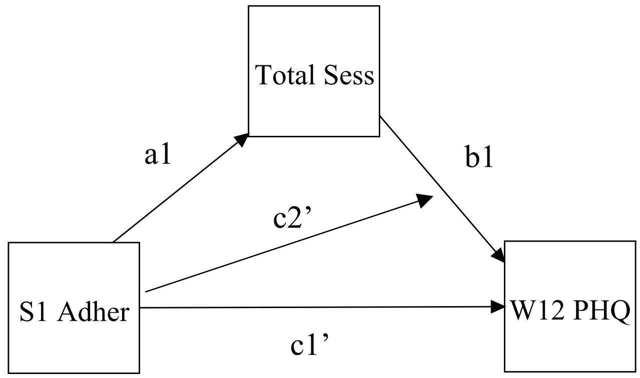


Figure 8. Moderated mediation model 1 with session one adherence moderating the relation between total sessions attended and week 12 PHQ-9 Scores. S1 Adher = session one adherence; Total Sess = total sessions attended; W12 PHQ = Week 12 PHQ-9 Score.

As anticipated from the correlation and regression results, there were no direct indirect, or moderating effects that emerged from the estimation of the model. All relations among variables were quite small, suggesting that MBC adherence at session one was not a predictor of depression symptom scores at week 12, and total sessions attended had no impact on this relation as a mediator variable. As noted above, however, the study was not powered to detect small effect sizes, which may have limited the identification of a mediating effect.

Table 43. Path estimates for mediation model 1.

Path	Estimate	Standard Error	*t* statistic	*p* value
a_1	-0.106	0.160	-0.663	0.508
b_1	0.731	0.648	1.128	0.259
c_1' (direct effect)	1.278	1.915	0.668	0.504
c_2' (interaction)	-0.509	0.462	-1.103	0.270

Note. a_1 = relation between total sessions and session 1 adherence; b_1 = relation between week 12 PHQ-9 score and total sessions; c_1' = direct effect of session 1 adherence on week 12 PHQ-9 score; c_2' = interaction effect of session 1 adherence and total sessions on week 12 PHQ-9 scores (moderated mediation effect).

There were also no conditional indirect effects in the estimated model (see Table 44 below), suggesting that the relation between week 12 PHQ-9 scores and total sessions was not moderated by level of clinician MBC adherence at session one.

Table 44. Conditional indirect effects for mediation model 1.

	Estimate	Standard Error	*t* statistic	*p* value
No Adherence (Score = 0)	-0.077	0.135	-0.571	0.568
Medium Adherence (Score = 1)	-0.023	0.061	-0.383	0.702
High Adherence (Score = 2 or 3)	0.003	0.048	0.071	0.943

Moderated Mediation Model 2 –Average Session 1 and Session 2 Adherence

An alternative moderated mediation model was explored with an independent variable of average session one and session two adherence, a mediator of total sessions attended, a dependent variable of week 12 PHQ-9, and controlling for baseline PHQ-9 score, education level, race, and gender (see Figure 9 below).

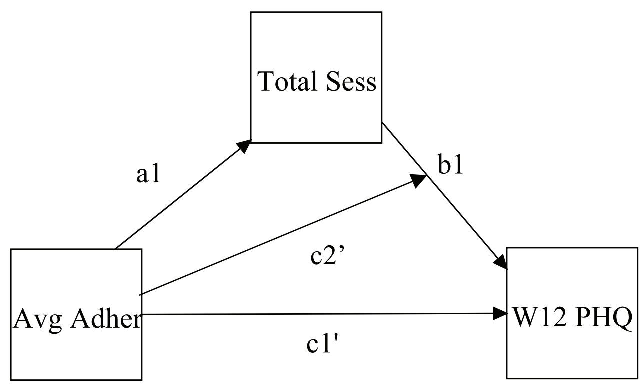


Figure 9. Moderated mediation model 2 with average session one and session two adherence moderating the relation between total sessions attended and week 12 PHQ-9 Scores. Avg Adher = average session one and session two adherence; Total Sess = total sessions attended; W12 PHQ = Week 12 PHQ-9 Score.

As in moderated mediation model one, there were no direct or indirect effects with the change in independent variable from session one adherence alone to average session one and session two adherence. There were also no conditional indirect effects for zero, medium, or high average session one and session two adherence.

Table 45. Path estimates for mediation model 2.

Path	Estimate	Standard Error	*t* statistic	*p* value
a_1	-0.040	0.138	-0.288	0.773
b_1	0.605	0.576	1.050	0.294
c_1’ (direct effect)	0.709	1.676	0.423	0.672
c_2’ (interaction)	-0.363	0.409	-0.887	0.375

Note. a_1 = relation between total sessions and session 1 adherence; b_1 = relation between week 12 PHQ-9 score and total sessions; c_1’ = direct effect of session 1 adherence on week 12 PHQ-9 score; c_2’ = interaction effect of session 1 adherence and total sessions on week 12 PHQ-9 scores (moderated mediation effect).

Table 46. Conditional indirect effects for mediation model 2.

	Estimate	Standard Error	*t* statistic	*p* value
No Adherence (Score = 0)	-0.024	0.093	-0.259	0.796
Medium Adherence (Score = 1)	-0.010	0.045	-0.212	0.832
High Adherence (Score = 2 or 3)	-0.002	0.030	-0.079	0.937

Moderated Mediation Model 3 – Dichotomous Adherence Variable

Given the significant percentage of clinicians not using MBC at session one (i.e. adherence scores of “0”), a third moderated mediation model was explored with a dichotomous independent variable coded “1” if clients received at least some MBC adherence (score of “1”, “2”, or “3”) at session one or “0” if they did not receive any MBC at session one (MBC adherence score of “0”; see Figure 10).

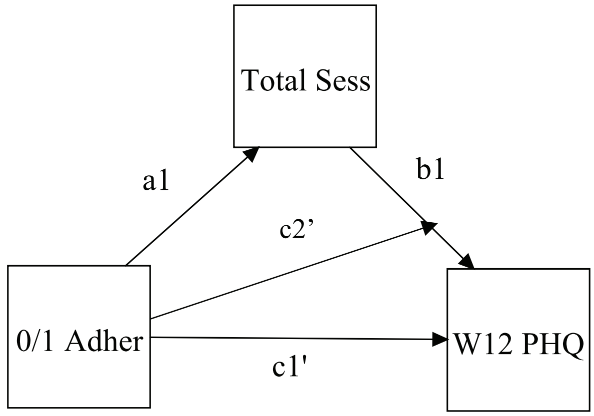


Figure 10. Moderated mediation model 3 with dichotomous adherence variable moderating the relation between total sessions attended and week 12 PHQ-9 Scores. 0/1 Adher = dichotomous adherence; Total Sess = total sessions attended; W12 PHQ = Week 12 PHQ-9 Score.

As observed above, there were no direct or indirect effects, suggesting no relation between dichotomous session one adherence and week 12 PHQ-9 and no mediating effect of total number of sessions. There were also no conditional indirect effects, suggesting that the relation between total sessions and week 12 PHQ-9 score is not moderated by adherence level (i.e. adherence of “0” or “1”).

Table 47. Path estimates for mediation model 3.

Path	Estimate	Standard Error	*t* statistic	*p* value
a_1	0.057	0.291	0.195	0.845
b_1	0.565	0.590	0.958	0.338
c_1’ (direct effect)	2.207	2.821	0.782	0.434
c_2’ (interaction)	-0.432	0.674	-0.641	0.522

Note. a_1 = relation between total sessions and session 1 adherence; b_1 = relation between week 12 PHQ-9 score and total sessions; c_1’ = direct effect of session 1 adherence on week 12 PHQ-9 score; c_2’ = interaction effect of session 1 adherence and total sessions on week 12 PHQ-9 scores (moderated mediation effect).

Table 48. Conditional indirect effects for mediation model 3.

	Estimate	Standard Error	*t* statistic	*p* value
No Adherence (Score = 0)	0.032	0.213	0.150	0.880
Adherence (Score = 1)	0.008	0.074	0.102	0.919

Exploratory Analyses – Direct Effect of Adherence on Outcomes for High and Low Attending Clients

Given the lack of moderated mediation, exploratory analyses were performed to determine whether clients with "low" session attendance (total sessions less than or equal to two) and clients with "high" session attendance (total sessions greater than two) demonstrated differences in depression symptom outcomes or differences in the relation between session one adherence and week 12 PHQ-9 scores. Both low (N = 41) and high attendance (N = 47) clients demonstrated statistically and clinically significant improvement in depression symptoms across 12 weeks of treatment. High and low attendance clients did not have differences in week 12 outcomes, with both groups of clients having moderate depression symptoms at week 12.

Table 49. Mean differences across treatment for low (N = 41) and high (N=47) attendance clients.

	M (SD)	*t*	*p* value	Average Mean Difference	Cohen's *d*
Low Attendance (N = 41)					
Baseline PHQ-9 vs.	17.91(4.58)	-3.97	0.001**	-5.63	1.07
Week 12 PHQ-9	11.46(7.16)				
High Attendance (N = 47)					
Baseline PHQ-9 vs.	16.73(4.14)	-6.27	0.000***	-5.43	1.00
Week 12 PHQ-9	11.61(5.93)				

Note. ** $p < 0.01$; *** $p < 0.001$.

Table 50. Mean differences in week 12 PHQ-9 outcomes for low (N = 41) and high (N=47) attendance clients.

	M(*SD*)	*t*	*p* value	Cohen's *d*
Low Attendance Week 12 PHQ-9	11.46(7.16)	-0.08	0.93	0.02
High Attendance Week 12 PHQ-9	11.61(5.93)			

Session one adherence did not predict PHQ-9 outcomes for either the low or high attendance clients. Compared to white clients, non-white clients who were high attenders had slightly lower week 12 PHQ-9 scores. No other relations were observed among variables, suggesting that adherence was not a predictor of outcomes, regardless of number of sessions attended by clients.

Table 51. Predictors of outcome (Week 12 PHQ-9) for low attendance clients ($N = 41$).

Predictor	Estimate	Standard Error	t statistic	p value	R^2	*p value*
DV: Week 12 PHQ-9						
Baseline PHQ-9	0.557	0.152	3.673	0.000***	0.149	0.046*
Gender	-1.739	3.622	-0.480	0.631		
Race	1.483	1.876	0.790	0.429		
Years Education	-0.213	0.424	-0.502	0.616		
Session 1 Adherence	-0.100	1.147	-0.087	0.930		

Note. *$p < 0.05$; ***$p < 0.001$.

Table 52. Predictors of outcome (Week 12 PHQ-9) for high attendance clients (N = 47).

Predictor	Estimate	Standard Error	t statistic	p value	R^2	p value
DV: Week 12 PHQ-9						
Baseline PHQ-9	0.428	0.162	2.642	0.008**	0.269	0.035*
Gender	-0.015	0.141	-0.106	0.915		
Race	-0.083	0.022	-3.731	0.000***		
Years Education	-0.114	0.100	-1.150	0.250		
Session 1 Adherence	-0.121	0.112	-1.085	0.278		

Note. *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Study 3 Discussion

Contrary to initial hypotheses, although clients demonstrated reductions in depression symptoms across 12 weeks of psychotherapy, there was no direct effect of early session adherence to MBC (session one or average session one and session two) on week 12 PHQ-9 scores when controlling for client baseline PHQ-9, gender, race, and years of education. Increased session attendance also failed to mediate the relation between clinician MBC adherence at therapy session one (independent variable) and client symptom outcomes (dependent variable) (**H1**), though the study was underpowered to detect paths with small effect sizes. Additionally, clinician MBC adherence was not a moderator of the relation between session attendance and client outcomes (**H2**).

It is perhaps surprising that MBC adherence did not have a direct effect on symptoms given the strong evidence for MBC's effectiveness in enhancing depression outcomes (Scott & Lewis, 2014). However, further exploration of clinician's MBC adherence showed that clients attended very few sessions ($M = 3.11$) and clinicians often failed to use MBC in those sessions. Only 46% of attended client sessions included any MBC (i.e., at least administering the PHQ-9), and only 9% of sessions attended by clients included clinician review and/or discussion of the PHQ-9 scores, elements that seem to truly enhance the effect of MBC (Lambert et al., 2003). Bickman and colleagues (2016) highlighted the potential for a dose-response relation between MBC and symptoms, thereby suggesting that a certain amount of clinician MBC use both within and across therapy sessions is needed in order to achieve change. The overall low adherence to MBC early in therapy found in this study may explain why early MBC was not associated with outcomes. This low adherence may be partially due to the design of the R01 parent study, as the parent study sought to identify whether and how much clinicians opted to implement MBC and therefore did not incorporate methods to ensure adherence occurred for mediation testing. Future research is needed to identify the level of MBC adherence required to achieve enhanced depression symptom change in order to more formally test moderated mediation effects with an adequate dosage of MBC intervention. In specific, additional evaluation is needed to determine when in treatment, how frequently, and what level of MBC adherence is optimal in order to maximize symptom change.

Modern approaches to mediation diverge from the traditional Baron and Kenny (Baron & Kenny, 1986) approach and suggest that a direct effect is unnecessary to explore mediation (Hayes, 2013). As a result, mediation models were explored in this study to determine the potential role of enhanced treatment engagement (via number of sessions attended) as a mechanism of action of MBC. Session attendance did not emerge as a mediator, suggesting that the data did not support enhanced treatment engagement as a mechanism, at least in how it was operationalized in this study. The failure to identify a direct effect may be due to the limited application of MBC across sessions. However, clients who only attended a maximum of two sessions demonstrated comparable depression symptom change to clients who attended more than two sessions. While evidence suggests that early attrition from psychotherapy leads to poor outcomes for clients (Cahill et al., 2003; Simpson et al., 1995), findings from this study suggest that a high dosage of psychotherapy and MBC may not be necessary for some clients to achieve clinically significant change. It may be the case that some clients benefit from very brief psychotherapy (i.e. one or two sessions). Although literature supports greater client benefit from shorter term psychotherapy (Cuijpers, Huibers, Ebert, Koole, & Andersson, 2013) and a "sudden gains" phenomenon in which many clients exhibit clinically significant change early in treatment (Busch, Kanter, Landes, & Kohlenberg, 2006), few studies have explored whether one or two sessions of psychotherapy is enough for some clients to achieve symptom change. Some evidence suggests that there may be two groups of clients who drop out early from treatment: one group with severe symptoms and significant barriers to treatment attendance (Barrett, Chua, Crits-Christoph, Gibbons, & Thompson, 2008) and one group with early symptom improvement or remission (Krishnamurthy, Khare, Klenck, & Norton, 2015; Lutz et al., 2009). Given the high demands for depression services and low client attendance in community mental health care, further exploration is warranted to evaluate the utility of very brief psychotherapy, perhaps guided by MBC to select optimal treatment targets and identify clients most likely to benefit from brief treatment.

The findings highlighted in this study may also be due to total session attendance not being the most appropriate indicator of treatment engagement. Alternatively, enhanced treatment engagement may not be a mechanism of action of MBC. Per the former, treatment engagement is also comprised of client participation in session and clinician-client alliance (Lindsey et al., 2014), two indicators that were not measured in this study and may require additional exploration as possible mediators of MBC's effectiveness. Per the latter, it may be the case that other putative mechanisms of action such as enhanced client symptom understanding (Dowrick et al., 2009), more accurate assessment (Sapyta et al., 2005), and/or enhanced "dosage" of psychotherapy interventions (Wolpert et al., 2016) may better explain how MBC produces symptom change in depression. Overall, treatment engagement, as well as the other putative mechanisms highlighted above, warrant further exploration as potential mediators of the relation between therapist MBC adherence and depression outcomes.

There are also several issues related to therapist MBC adherence that may have influenced the findings presented in this study. Although adherence serves as a measure of clinician application of MBC, it does not capture how well a clinician actually uses MBC in each clinical session (i.e. MBC competence; Schoenwald et al., 2011). Competence in using MBC may ultimately be more important for enhancing clinical outcomes, and should therefore be explored as a measure of overall MBC fidelity. Additionally, this study utilized early session measures of MBC adherence as an independent variable in the mediation model in order to ensure that the adherence measure preceded the majority of treatment sessions attended and depression symptom change given the putative mediator under investigation. MBC adherence may actually be more important at later sessions, perhaps as a tool to address a client's lack of progress in ongoing treatment or to signal a need for treatment changes (Lambert et al., 2003; Simon et al., 2012). It may be important for future research to employ more sophisticated cross-lagged panel mediation models in order to identify when depression symptom change occurs, when MBC adherence might be most important (i.e. at what therapy sessions), and how MBC adherence works to produce change across multiple time points (Preacher, 2015).

Limitations

As noted above, one of the biggest limitations of this study was its small sample size. The study was underpowered to identify estimates with small effect sizes for the early session adherence to mediator path (path a_1), as path estimates were below 0.12 in all models (see power analysis in Study 3 Methods). The sample explored in this study (*N* = 88 clients) was also not sufficiently powered to detect mediation effects with small effect sizes, therefore the analysis may have failed to identify indirect effects. Future research should explore total sessions attended as a putative mediator and mechanism of action of MBC with greater MBC adherence as well as a larger client sample size to increase statistical power.

This study also only included clients enrolled from 10 of the 12 sites recruited in the parent R01 study. All mediation analyses will be rerun with the full sample of new, enrolled clients across all 12 sites as additional data becomes available in the ongoing parent study. Additionally, this study explored only the first 12 weeks of therapy for new clients who enrolled in the parent R01 study at 10 community behavioral health sites. As a result, the sample of clients explored in this study may not generalize to other clients across other mental health treatment settings.

Conclusions

This study sought to evaluate whether enhanced session attendance served as a mechanism of action of MBC's ability to enhance depression symptom change. The mediation models explored in this study failed to identify an association between MBC adherence in early treatment sessions and improved depression outcomes and did not find evidence for session attendance as a mechanism of action of MBC. However, all clients demonstrated clinically significant improvement in depression symptoms across 12 weeks of treatment regardless of client MBC adherence in the first two sessions or level of session attendance. These results may have important implications for guiding future research with larger sample sizes of clients in order to identify both the level of MBC adherence needed to enhance depression symptom change as well as to enable further testing of enhanced session attendance and other putative mechanisms of action of MBC. Additionally, these study findings suggest a need for further research exploring how a subset of clients experience clinically significant change early in care (one or two sessions). In sum, the study results presented herein serve as a first step in testing MBC's mechanisms of action in order to understand key MBC components and maximize the effect of MBC on depression for clients across settings.

General Discussion

MBC is a potentially powerful EBP that could serve as a minimal intervention needed to produce change and begin to reduce the global burden of disease association with depression (Glasgow et al., 2014; Organization, 2016). The studies presented herein were some of the first, to our knowledge, to understand clinician in-session responses to MBC feedback, to evaluate patterns of clinician use of MBC in community mental health settings, and to formally test one putative MBC mechanism of change. Overall study findings suggest that clinicians generally respond to feedback in line with the FIT model, but that the complexities of clinician assessment and decision-making processes and client responses to feedback may warrant additional exploration. There also appear to be observable patterns of clinician MBC adherence post training, and that clinicians demonstrate substantial variation in their use of MBC in session. In specific, there appears to be at least two common patterns of MBC use among community clinicians: those who start high and maintain their use and those who start low and decrease their use over time. However, the studies, though underpowered to detect some relations, failed to identify treatment engagement as a mechanism of change for MBC. The dosage of MBC required to produce symptom change also remains unclear.

Additional research is needed to elucidate MBC's key components and causal processes in order to maximize MBC's effective implementation in community settings. In specific, broader evaluations of fidelity that include clinician adherence, competence, and differentiation may be helpful for identifying when and how MBC produces symptom change. Additional person-centered analyses may also be useful to integrate both qualitative exit interview and quantitative adherence data such that class differences in in-session MBC use could be identified. This approach may provide further context for why MBC adherence failed to be associated with depression symptom outcomes. Finally, all three studies presented herein could have benefitted from a larger sample size and more complete data. Better quality data at the client-level could enable greater variation in clinician exit interview responses to receiving feedback, higher potential for identifying additional classes of clinicians with unique patterns of MBC use, and greater power to detect mediation. A larger sample size could also enable the use of sophisticated longitudinal cross-lagged panel mediation testing, thereby identifying whether and when in treatment putative mechanisms such as treatment engagement have the greatest impact on the relation between MBC use and depression symptom change.

Next Steps and the Future of MBC Research

Recent literature has suggested that mental health care is at a "tipping point" such that the wide availability of measures and benefits of MBC are likely to tip mental health practice toward the regular use of MBC. In fact, not using MBC has been presented as a disservice to both the clients who serve to benefit as well as the organizations and health care systems who base their quality assurance and treatment offering decisions on treatment effectiveness data (Fortney et al., 2016). Priority has been placed on developing brief, psychometrically validated self-report measures as well as advanced technological solutions via user-centered design approaches for maximizing the reach and feasibility of MBC implementation (Fortney et al., 2016; Lyon & Lewis, 2016). Additionally, MBC is marketed as an EBP that is efficient to use in session and requires less burden on clinicians with respect to cost, resources, and training requirements when compared to complex treatments like Cognitive Behavioral Therapy (CBT; Scott & Lewis, 2014). In sum, the conditions appear ripe for rapid uptake of MBC practices across settings, yet successful community implementation remains challenging and much is still unknown about the key components of MBC that will maximize outcomes.

Despite MBC's lower complexity compared to CBT and other EBPs, it is not without its challenges with respect to training and implementation. In fact, clinicians highlight many of the same barriers to MBC use that they have with more complex EBPs, including time limitations, lack of quality training, limited ongoing supervision, and few resources (including technology; Scott & Lewis, *in prep*). Many of these clinician concerns may not be unfounded, as advanced technological systems that facilitate MBC can be prohibitively expensive to purchase, maintain, and integrate with proprietary electronic health record software. Even if clinicians gain access to user-friendly MBC technologies, they still likely require high quality training with active learning strategies and ongoing supervision to maintain use with complex community clients. With these barriers in mind, it would seem like an insurmountable task to implement MBC in the community mental health settings with the most need for quality depression treatment. However, study findings highlighted above note the potential for a subset of clinicians to have high, MBC use that is sustained over at least a 5-month period.

A key next step in enhancing the potential for broad reach of MBC is to learn more about the individuals within an organization who are high, maintaining users of MBC as identified in the present studies. These potential EBP champions (Kitson et al., 1998) appear to be successfully using MBC despite the many barriers. Leveraging the MBC skills, training background, and social influence of high use clinicians may be especially influential for encouraging a shift in norms towards broad MBC use. For example, clinics could facilitate additional MBC training opportunities for champions, who could then provide ongoing consultation to their colleagues regarding how to overcome barriers to MBC use. If clinic norms could shift to elevate the importance of EBPs, routine implementation of MBC would perhaps not feel so divergent from current practices (Gray, Joy, Plath, & Webb, 2015).

Next, the most effective studies of MBC in both psychotherapy and pharmacotherapy highlight the utility of clinical decision support tools to guide clinician decision-making upon receipt of MBC feedback (Lambert et al., 2001; Trivedi et al., 2006). These clinical-decision support tools can take the form of decision trees that would guide clinicians towards appropriate interventions for responding to positive or negative feedback. Community clinicians may require additional support for both identifying an expected standard of symptom change for their clients and for deciding what to do in the moment when they receive feedback that an especially challenging client is not making progress. As highlighted by the FIT model (Kluger & DeNisi, 1996), such support may enhance clinician motivation and self-efficacy in responding to feedback by trying new, evidence-based treatment approaches, even with complex clients who have failed to respond to previous interventions. However, additional research is needed to identify the optimal standards of change and interventions to be integrated into such clinical decision support tools targeted for community settings.

Finally, MBC implementation could benefit from the provision of additional resources for training and supervision in EBPs both in community mental health clinicians' graduate programs as well as in the clinics where they are employed. The passage of the Patient Protection and Affordable Care Act (PPACA) has placed greater emphasis on enhancing broad access to quality mental health care, an initiative that aligns with the goals of the field of implementation science (Obama, 2016). The PPACA specifically prioritizes screening for mental health symptoms and use of MBC approaches in both primary care and in mental health care settings. However, there are still significant disparities in the availability of high quality, evidence-based mental health screening and care, especially for rural populations and individuals from racial or ethnic minority backgrounds (Alegría et al., 2008; Priester et al., 2016). Some have suggested that paraprofessional clinicians could be trained to meet these needs (Montgomery, Kunik, Wilson, Stanley, & Weiss, 2010), but it is still challenging and costly to provide consistent EBP training and adequate wages to build a capable workforce of paraprofessional and graduate-level clinicians (Mechanic & Olfson, 2016). Additionally, the use of paraprofessionals would not solve the issue of medical doctors practicing in primary care who also require training in the use of MBC as a screening and monitoring tool for depression symptoms (Kearney, Wray, Dollar, & King, 2015). Until significant systemic changes occur to provide additional support for clinicians on the front lines of service, MBC and other EBP implementation efforts are likely to face significant challenges and the global burden of depression will likely persist.

Conclusions

In sum, the studies presented herein were some of the first to elucidate how MBC functions in session to improve depression symptoms, with the ultimate goals of informing efforts to widely implement MBC and enhancing outcomes for community clients. The variation in clinician in-session adherence to MBC over time and limited association of MBC with clinical outcomes in these studies suggests additional efforts are warranted to identify how much MBC is needed to produce change and how to encourage clinicians to successfully implement MBC at an effective level. If research is able to identify the core components of MBC and community mental health norms shift to facilitate EBP use, we may truly be at a “tipping point” for broad and effective appication of MBC for depression with clients most in need.

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Appendices

Appendix A. Study measures collected through the parent R01 study.

Domain	Measures & Indicators	Interval
Client Measures		
Demographics	Developed by Lewis & Simons (2011) to assess clinician demographic information and training background.	Baseline
Depression Severity	*Patient Health Questionnaire-9* (PHQ-9; Kroenke, Spitzer, & Williams, 2001). The PHQ-9 is a 9 item self-report that assesses depression severity and has demonstrated good internal consistency (α=.85-.89) and sensitivity to change (Löwe, Kroenke, Herzog, & Gräfe, 2004).	All Sessions by Clinicians; Baseline and Week 12 by Research Staff
Client Treatment Engagement (*mediator*)	Number of sessions attended in the Centerstone EHR.	Monthly EHR Queries
Clinician Measures		
Demographics	Developed by Lewis & Simons (2011) to assess clinician demographic information and training background.	Baseline
MBC Adherence	A measure of MBC adherence coded as 0-did not administer, 1-administered only, 2-administered and reviewed scored, and 3- administered, reviewed scores, and discussed with client in session – collected from the HER	All Sessions
Behavioral Approaches to MBC	Qualitative Clinician exit interviews will be conducted with clinicians to identify the alignment of clinician use of MBC with the FIT model, to obtain details of how clinicians employed MBC, and to expand upon data collected from clients on MBC use in session.	5 months following MBC training

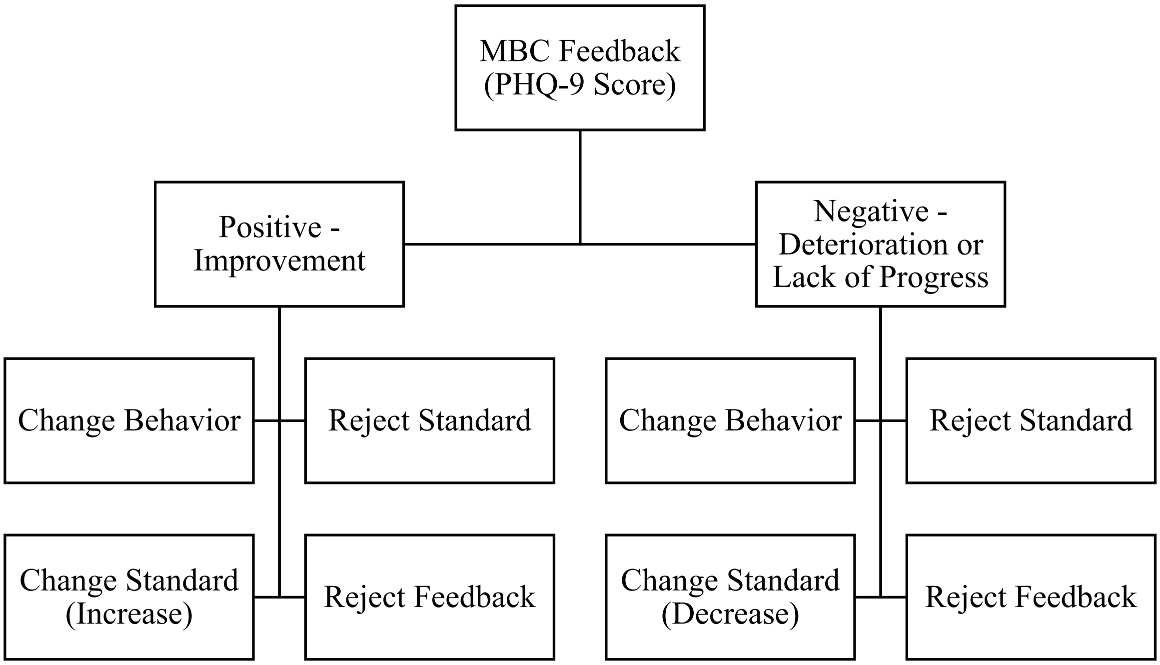
Appendix B. List of DSM diagnostic codes for inclusion in the parent R01 study.

293.83	DEPRESSIVE DISORDER DUE TO ANOTHER MEDICAL CONDITION WITH DEPRESSIVE FEATURES
293.83	DEPRESSIVE DISORDER DUE TO ANOTHER MEDICAL CONDITION WITH MAJOR DEPRESSIVE-LIKE EPISODE
293.83	DEPRESSIVE DISORDER DUE TO ANOTHER MEDICAL CONDITION WITH MIXED FEATURES
296.20	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE UNSPECIFIED
296.20	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE UNSPECIFIED DEGREE
296.21	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE MILD
296.21	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE MILD DEGREE
296.22	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE MODERATE
296.22	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE MODERATE DEGREE
296.23	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE SEVERE
296.23	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE SEVERE DEGREE WITHOUT MENTION OF PSYCHOTIC BEHAVIOR
296.23	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE SEVERE WITHOUT PSYCHOTIC FEATURES
296.24	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE SEVERE DEGREE SPECIFIED AS WITH PSYCHOTIC BEHAVIOR

296.24	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE SEVERE WITH PSYCHOTIC FEATURES
296.24	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE WITH PSYCHOTIC FEATURES
296.25	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE IN PARTIAL OR UNSPECIFIED REMISSION
296.25	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE IN PARTIAL REMISSION
296.26	MAJOR DEPRESSIVE DISORDER SINGLE EPISODE IN FULL REMISSION
296.30	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE UNSPECIFIED
296.30	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE UNSPECIFIED DEGREE
296.30	MAJOR DEPRESSIVE DISORDER RECURRENT UNSPECIFIED
296.31	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE MILD
296.31	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE MILD DEGREE
296.31	MAJOR DEPRESSIVE DISORDER RECURRENT MILD
296.32	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE MODERATE
296.32	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE MODERATE DEGREE
296.32	MAJOR DEPRESSIVE DISORDER RECURRENT MODERATE
296.33	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE SEVERE

296.33	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE SEVERE DEGREE WITHOUT MENTION OF PSYCHOTIC BEHAVIOR
296.33	MAJOR DEPRESSIVE DISORDER RECURRENT SEVERE WITHOUT PSYCHOTIC FEATURES
296.34	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE SEVERE DEGREE SPECIFIED AS WITH PSYCHOTIC BEHAVIOR
296.34	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE WITH PSYCHOTIC FEATURES
296.34	MAJOR DEPRESSIVE DISORDER RECURRENT SEVERE WITH PSYCHOTIC FEATURES SPECIFY: MOOD-CONGRUENT
296.35	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE IN PARTIAL OR UNSPECIFIED REMISSION
296.35	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE IN PARTIAL REMISSION
296.35	MAJOR DEPRESSIVE DISORDER RECURRENT IN PARTIAL REMISSION
296.36	MAJOR DEPRESSIVE DISORDER RECURRENT EPISODE IN FULL REMISSION
296.36	MAJOR DEPRESSIVE DISORDER RECURRENT IN FULL REMISSION
296.80	ATYPICAL DEPRESSIVE DISORDER
296.90	UNSPECIFIED EPISODIC MOOD DISORDER
300.4	DYSTHYMIC DISORDER EARLY ONSET WITH ATYPICAL FEATURES

300.4	DYSTHYMIC DISORDER EARLY ONSET WITHOUT ATYPICAL FEATURES
300.4	DYSTHYMIC DISORDER LATE ONSET WITH ATYPICAL FEATURES
300.4	DYSTHYMIC DISORDER LATE ONSET WITHOUT ATYPICAL FEATURES
300.4	PERSISTENT DEPRESSIVE DISORDER (DYSTHYMIA)
301.13	CYCLOTHYMIC DISORDER
311	DEPRESSIVE DISORDER NOS
311	DEPRESSIVE DISORDER NOT ELSEWHERE CLASSIFIED
311	OTHER SPECIFIED DEPRESSIVE DISORDER
311	UNSPECIFIED DEPRESSIVE DISORDER



Appendix C. FIT model for clinician responses to feedback.

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Education

Northwestern University **July 2017- June 2018**
Feinberg School of Medicine, Chicago, IL
Clinical Psychology Internship
Training Director: Dr. Mark Reinecke, Ph.D., ABPP

Indiana University, Bloomington, IN **Aug 2012- June 2018**
Ph.D. in Clinical Psychology
Training, Research, and Implementation in Psychology Lab
Adviser: Cara C. Lewis, Ph.D.
Dissertation Title: Identifying the Mechanisms of Change and In-Session Therapist Fidelity in Measurement-Based Care for Depression (*defended June 2017*)

University of Pennsylvania, Philadelphia, PA **2009-2012**
College of Liberal and Professional Studies: Post-Baccalaureate Undergraduate Program
Special Topics in Abnormal Psychology: Body Image (Fall 2010)
Applied Regression and Analysis of Variance (Fall 2011)

Cornell University, Ithaca, NY **2005-2009**
Bachelor of Arts Degree in Biological Sciences
Concentration in Neurobiology and Behavior

Grant Funding

Ruth L. Kirschstein National Research Service Award (NRSA) Fellowship **2016-2017**
NIMH 1F31MH111134-01
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Indiana University-Bloomington
Title: Identifying the Mechanisms of Change in Measurement Based Care for Depression. $43,576

NRSA Institutional Predoctoral Training Fellowship (T32) **2015-2016**
NIMH T32MH103213-1A1,
Role: Predoctoral Fellow
PI: William Hetrick, Ph.D.
Title: Training in Clinical Translational Science: Maximizing the Public Health Impact. $22,920

Indiana Clinical and Translational Sciences Institute (CTSI) **Summer 2015**

Community and Urban Health Protocol Development Team Grant
Role: Summer Fellow
ICTSI NIH/NCRR UL1TR001108
PI: Cara Lewis, Ph.D.
Title: Evaluating Progress Monitoring Implementation in Youth Residential Settings, $4,000

Indiana University Richard McFall Summer Research Fellowship **Summer 2014**
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Funded by Indiana University-Bloomington. $4,000

Grant Funding as Research Specialist/Project Coordinator

NIMH 1R01MH103310-01A1 **2014-2018**
Role: Measurement-Based Care Trainer, Consultant, Graduate Student Researcher
PI: Cara Lewis, Ph.D.
Indiana University – Bloomington
Title: R01: Standardized versus Tailored Implementation of Measurement Based Care for Depression

Wolverine Human Services CBT Implementation Grant **2013-2018**
Role: Co-Investigator, Measurement-Based Care Trainer
PI: Cara Lewis, Ph.D.
Indiana University – Bloomington
Title: Tailored Approach to Implementation of Cognitive Behavioral Therapy for Youth in Residential Treatment Settings, Funded by Wolverine Human Services.

NIMH R34MH085841 **2010-2012**
Role: Project Coordinator/Research Specialist
PI: Mary Beth Connolly Gibbons, Ph.D.
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Title: The Development of a Therapist Feedback System for MDD in Community Mental Health

AHRQ R01HS018440 **2010-2012**
Role: Project Coordinator/Research Specialist
PI: Mary Beth Connolly Gibbons,
University of Pennsylvania Center for Psychotherapy Research
Title: A Comparison of Cognitive and Dynamic Therapy for MDD in Community Settings

NIMH R24MH070698 **2010-2012**
Role: Research Specialist
PI: Paul Crits-Christoph
University of Pennsylvania Center for Psychotherapy Research
Title: Psychotherapy for Major Depression in the Community

NIMH R01MH092363 **2010-2012**
Role: Research Specialist
PI: Paul Crits-Christoph
University of Pennsylvania Center for Psychotherapy Research
Title: The Mechanisms of Cognitive and Dynamic Therapy in Community Settings

NIMH R34MH085817 **2010-2012**
Role: Research Specialist
PI: Paul Crits-Christoph
University of Pennsylvania Center for Psychotherapy Research
Title: Development of a Tool to Measure Consumer Preferences in MDD Treatment

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Awards and Honors

Recipient, Indiana Psychological Association Student Poster Award **2012**
Recipient, Indiana University Provost's Travel Award for Women in Science **2013-2016**
Recipient, First Place Student Poster Award, Association for Behavioral and Cognitive Therapies Dissemination and Implementation Special Interest Group **2014, 2017**

Peer Reviewed Publications

Lewis, C. C., **Scott, K.,** & Marriott, B. R. (2018). A methodology for generating a tailored implementation blueprint: an exemplar from a youth residential setting. *Implementation Science*, *13*(1), 68.

Walsh, L. M., Roddy, M. K., **Scott, K.,** Lewis, C. C., & Jensen-Doss, A. (2018). A meta-analysis of the effect of therapist experience on outcomes for clients with internalizing disorders. *Psychotherapy Research*, 1-14.

Lewis, C. C., Puspitasari, A., Boyd, M. R., Scott, K., Marriott, B. R., Hoffman, M., ... & Kassab, H. (2018). Implementing measurement based care in community mental health: a description of tailored and standardized methods. *BMC Research Notes*, *11*(1), 76.

Rozek, D. C., Serrano, J. L., Marriott, B. R., **Scott, K.** Hickman, L. B., Brothers, B. M., Lewis, C. C, & Simons, A. D. (2018). Cognitive behavioral therapy competency: Pilot data from a comparison of multiple perspectives. *Behavioural and cognitive psychotherapy*, *46*(2), 244-250.

Boyd, M. R., Lewis, C. C., **Scott, K.,** Krendl, A., & Lyon, A. R. (2017). The creation and validation of the Measure of Effective Attributes of Trainers (MEAT). *Implementation Science*, *12*(1), 73.

Lewis, C. C., Marti, C. N., Marriott, B. R., **Scott, K.,** & Ayer, D. (2017). Patterns of practice in community mental health treatment of adult depression. *Psychotherapy Research*, 1-8.

Jacinto, S. B., Lewis, C. C., Braga, J. N., & **Scott, K.** (2016). A conceptual model for generating and validating in-session clinical judgments. *Psychotherapy Research*, 1-15.

Lewis, C., Darnell, D., Kerns, S., Monroe-DeVita, M., Landes, S. J., Lyon, A. R., ... **Scott, K.** & Puspitasari, A. (2016). Proceedings of the 3rd Biennial Conference of the Society for Implementation Research Collaboration (SIRC) 2015: advancing efficient methodologies through community partnerships and team science. *Implementation Science*, *11*(1), 85.

Lewis, C. C., **Scott, K.,** Marti, C. N., Marriott, B. R., Kroenke, K., Putz, J. W., ... & Rutkowski, D. (2015). Implementing measurement-based care (iMBC) for depression in community mental health: a dynamic cluster randomized trial study protocol. *Implementation Science*, *10*(1), 1-14.

Scott, K., Klech, D., Lewis, C. C., & Simons, A. D. (2015). What did they learn? The effects of a brief cognitive behavioral therapy workshop on community therapists' knowledge. *Community Mental Health*, 1-6.

Scott, K., & Lewis, C. C. (2015). Using measurement-based care to enhance any treatment. *Cognitive and Behavioral Practice*, *22*(1), 49-59.

Lewis, C. C., **Scott, K.**, & Hendricks, K. (2014). A model and guide for evaluating supervision outcomes in cognitive–behavioral therapy-focused training programs. *Training and Education in Professional Psychology*, *8*(3), 165.

Connolly Gibbons, M. B., Thompson, S. M., **Scott, K.**, Schauble, L. A., Mooney, T., Thompson, D. L.,… Crits-Christoph, P. (2012). Supportive-expressive dynamic psychotherapy in the community mental health system: a pilot effectiveness trial for the treatment of depression. *Psychotherapy. 49*(3), 303-316.

Connolly Gibbons M. B., Rothbard A., Farris K. D., Wiltsey Stirman, S., Thompson S. M., **Scott K.**,…Crits-Christoph P. (2011). Changes in psychotherapy utilization among consumers of services for major depressive disorder in the community mental health system. *Administration and Policy in Mental Health and Mental Health Services Research, 38(6),* 495-503.

Goldstein L. A., Connolly Gibbons M. B., Thompson S. M., **Scott K.,** Heintz L. E., Green P.,…, Crits-Christoph P. (2010). Outcome assessment via handheld computer in community mental health: consumer satisfaction and reliability. *The Journal of Behavioral Health Services and Research, 38*(3)*,* 414-423.

Manuscripts Under Review

Scott, K., Lewis, C.C., Marti, C.N. (2018). *The treatment for adolescents with depression study: a growth mixture modeling reanalysis.* Manuscript under review.

Manuscripts In Preparation

Scott, K., Wahlen, S., Marriott, B.R., Lyon, A.R., & Lewis, C. C. (2017). *Longitudinal investigation of the theory of planned behavior on implementation of measurement based care.* Manuscript in preparation.

Scott, K., & Lewis, C. C. (2017). *An exploratory qualitative evaluation of factors influencing implementation of measurement-based care for depression in the community.* Manuscript in preparation.

Professional Presentations

Invited Lectures

Scott, K., McQuillan, M., & Rodriguez-Quintana, N. (2016, October). *Introduction to providing therapy and serving as a junior clinical psychologist.* Presentation in PSY-P 480 Intervention and Evaluation at the Indiana University Department of Psychological and Brain Sciences, Bloomington. IN.

Scott, K. (2016, March). *Empirically supported treatments for anxiety disorders*. Presentation in PSY-P 631 Intervention and Evaluation at the Indiana University Department of Psychological and Brain Sciences, Bloomington. IN.

Scott, K. (2016, April). *Measurement-based care.* Presentation in PSY-P 631 Intervention and Evaluation at the Indiana University Department of Psychological and Brain Sciences, Bloomington. IN.

Scott, K. (2015, November). *Implementation science overview.* Presentation in PSY-P 457 Psychotherapy: Empirically Supported Treatments at the Indiana University Department of Psychological and Brain Sciences, Bloomington. IN.

Scott, K. & Lewis, C. C. (2015, October). *Mechanisms of measurement-based care: Finding the core components of evidence-based practices.* Presentation at the Clinical Psychology colloquium meeting at the Indiana University Department of Psychological and Brain Sciences, Bloomington, IN

Scott, K. & Lewis, C. C. (2015, October). *Using social psychological theory and methods to inform implementation of evidence-based practices.* Presentation at the Social Psychology colloquium meeting at the Indiana University Department of Psychological and Brain Sciences, Bloomington, IN.

Scott, K. (2014, April). *Measurement based care and evidence based assessment*. Presentation in PSY-P631 Intervention Course at the Indiana University Department of Psychological and Brain Sciences, Bloomington. IN.

Scott, K. (2014, November). *Implementation science*. Presentation at the Clinical Science colloquium meeting at the Indiana University Department of Psychological and Brain Sciences, Bloomington, IN.

Lewis, C. C., & **Scott, K.,** (2012, October). *Implementation science: the role of social psychology.* Presentation at the Social Psychology colloquium meeting at the Indiana University Department of Psychological and Brain Sciences, Bloomington, IN.

National and International Conferences

Scott, K., Jarad, I., & Lewis, C. C. (2017, October). Patterns of practice and barriers to measurement-based care implementation with fidelity. Poster presented at the meeting of the Association for Behavioral and Cognitive Therapies, San Diego, CA.

Scott, K., Marriott, B., & Lewis, C. C. (2016, October). *Longitudinal investigation of the theory of planned behavior on implementation of measurement based care.* Poster presented at the meeting of the Association for Behavioral and Cognitive Therapies, New York, NY.

Scott, K., Marriott, B., & Lewis, C. C. (2015, November). *Using the theory of planned behavior to guide progress monitoring implementation.* Poster presented at the meeting of the Association for Behavioral and Cognitive Therapies, Chicago, IL.

Scott, K., Marriott, B., & Lewis, C. C. (2014, November). *Tailoring a cognitive behavioral therapy implementation protocol using mixed methods and conjoint analysis.* Symposium presented at the meeting of the Association for Behavioral and Cognitive Therapies, Philadelphia, PA.

Scott, K., & Lewis, C. C. (2014, November). *A social psychological approach to implementation of evidence-based practices in community settings.* Symposium presented at the meeting of the Association for Behavioral and Cognitive Therapies, Philadelphia, PA.

Scott, K., Dorsey, C., Marriott, B., & Lewis, C. C. (2014, November). *Psychometric validation of the impact on infrastructure survey.* Poster session presented at the meeting of the Association for Behavioral and Cognitive Therapies, Philadelphia, PA.

Scott, K., Lewis, C. C., Harris, H., Garibay, A. (2013, November). *A qualitative analysis of contextual factors influencing implementation of measurement based care.* Poster session presented at the meeting of the Association for Behavioral and Cognitive Therapies, Nashville, TN.

Scott, K., Garibay, A., Harris, H., Lewis, C. C. (2013, November). *A mixed methods analysis of predictors of measurement based care use in community mental health.* Poster session presented at the meeting of the Association for Behavioral and Cognitive Therapies, Nashville, TN.

Scott, K., & Lewis, C. C. (2013, November). *How to leverage measurement-based care: an empirical review with a case example.* Symposium presented at the meeting of the Association for Behavioral and Cognitive Therapies, Nashville, TN.

Scott, K., Lewis, C. C., & Ayer, D. (2012, October). *An analysis of therapist practice patterns from the clinical pathways for depression project.* Poster session presented at the meeting of the Indiana Psychological Association, Carmel, Indiana. *Recipient of the student poster award.*

Scott, K., Connolly Gibbons, M. B., Schauble, L. A., Thompson, S. M., Hamilton, J. L., Heintz, L. E., & Crits-Christoph, P. (2011, May). *Racial differences in psychotherapy utilization in the community mental health system*. Poster session presented at the meeting of the Society for the Exploration of Psychotherapy Integration, Washington, D.C.

Scott, K., Connolly Gibbons, M. B., Schauble, L. A., Thompson, D. L., & Crits-Christoph, P. (2011, September). *The development and psychometric analysis of the community therapist feedback questionnaire*. Poster session presented at the meeting of the North American Society for Psychotherapy Research, Banff, Alberta.

Scott, K., Connolly Gibbons, M. B., Schauble, L. A., Thompson, S. M., Heintz, L. E., Hamilton, J. L., & Crits-Christoph, P. (2011, June). *The development of community-friendly and self-report versions of the ways of responding questionnaire*. Poster session presented at the meeting of the Society for Psychotherapy Research, University of Bern, Switzerland.

Lewis, C. C., Marriott, B. R., & **Scott, K.** (2015, September). *Tailoring a cognitive behavioral therapy implementation protocol using mixed methods, conjoint analysis, and implementation teams.* Symposium presented at the Society for Implementation Research Collaboration Biennial Conference. Seattle, WA.

Marriott, B., **Scott, K.,** Lewis, C. C. (2014, November). *Assessing for differences in organizational context and attitudes across stakeholder levels in adolescent residential treatment settings*. Poster presented at the Association for Behavioral and Cognitive Therapies Dissemination and Implementation Special Interest Group Poster Session. Philadelphia, PA.

Lewis, C. C., Ayer, D., **Scott, K.,** Harrison, J., Hardy, M., & Pardue, A. (2012, November). *Preliminary data from the clinical pathways for depression project.* Symposium presented at the meeting of the Association for Behavioral and Cognitive Therapies, National Harbor, MD.

Connolly Gibbons, M. B., Mooney, T. K., Schauble, L. A., **Scott, K.**, Sadicario, J. S., Ring-Kurtz, S. & Crits-Christoph, P. (2012). *Predictors of treatment dropout in treatments for depression in the community mental health system.* Poster session submitted for presentation at the meeting of the Society for Psychotherapy Research, Virginia Beach, VA.

Mooney, T. K., Connolly Gibbons, M. B., Sadicario, J. S., Schauble, L. A., **Scott, K.**, Ring-Kurtz, S., ..., & Crits- Christoph, P. (2012). *Previous treatment moderating the relationship between expectations and outcome.* Poster session submitted for presentation at the meeting of the Society for the Exploration of Psychotherapy Integration, Chicago, IL.

Mooney, T. K., Connolly Gibbons, M. B., Sadicario, J. S., Schauble, L. A., **Scott, K.**, Ring-

Kurtz, S., ..., & Crits-Christoph, P. (2012). *Baseline predictors of credibility ratings for adult psychotherapies for different disorders.* Poster session submitted for presentation at the meeting of the Society for Psychotherapy Research, Virginia Beach, VA.

Connolly Gibbons, M. B., Ring-Kurtz, S., Schauble, L. A., **Scott, K.**, Thompson, D. L., Connors, D., & Crits-Christoph, P. (2011, September). *The challenges faced during the training phase of a psychotherapy comparative effectiveness study conducted in the community mental health system.* Paper presented at the meeting of the North American Society for Psychotherapy Research, Banff, Alberta.

Connolly Gibbons, M. B., **Scott, K.**, Schauble, L. A., Thompson, S. M., Hamilton, J. L., Heintz, L. E., & Crits-Christoph, P. (2011, May). *A pilot randomized trial of a community friendly supportive expressive psychotherapy versus treatment-as-usual in the treatment of depression in the community mental health system*. Poster session presented at the meeting of the Society for the Exploration of Psychotherapy Integration, Washington, D.C.

Heintz, L. E., Barrett, M. S., Connolly Gibbons, M. B., **Scott, K.**, Schauble, L. A., Thompson, S. M., & Crits-Christoph, P. (2011, May). *Predictors of treatment engagement in a community mental health center*. Poster session presented at the meeting of the Society for the Exploration of Psychotherapy Integration, Washington, D.C.

Schauble, L. A., Connolly Gibbons, M. B., **Scott, K.**, & Crits-Christoph, P. (2011, June). *A comparison of clinical diagnoses and structured clinical interview diagnoses in a community mental health setting.* Poster session presented at the meeting of the Society for Psychotherapy Research, University of Bern, Switzerland.

Schauble, L. A., Connolly Gibbons, M. B., **Scott, K.**, Thompson, S. M., Hamilton, J. L., Heintz, L. E., & Crits-Christoph, P. (2011, May). *An examination of racial differences in attitudes and expectations towards treatments for depression in the community mental health system*. Poster session presented at the meeting of the Society for the Exploration of Psychotherapy Integration, Washington, D.C.

Schauble, L. A., Connolly Gibbons, M. B., **Scott, K.**, Thompson, S. M., Hamilton, J. L., Heintz, L. E., & Crits-Christoph, P. (2011, September). *An analysis of the most common diagnostic discrepancies between clinical diagnoses and structured clinical interview diagnoses in a community mental health setting.* Poster session presented at the meeting of the North American Society for Psychotherapy Research, Banff, Alberta.

Thompson, S. M., Connolly Gibbons, M. B., Schauble, L. A., **Scott, K**., Heintz, L. E., Hamilton, J. L., & Crits- Christoph, P. (2011, May). *Changes in CCRT patterns over the course of cognitive and interpersonal therapies*. Poster session presented at the meeting of the Society for the Exploration of Psychotherapy Integration, Washington, D.C.

Clinical Training

Northwestern Medicine Stone Institute of Psychiatry **2017-2018**

Intern Clinician
Supervisors: Dr. Mark Reinecke, Ph.D., ABPP, Dr. Vicky Singh, Ph.D., Dr. John Stutesman, Psy.D.
Conducted Cognitive Behavioral Therapy and Dialectical Behavior Therapy in a community mental health center setting for patients with Bipolar Disorder, Severe Major Depressive Disorder, Anxiety Disorder, Panic Disorder, and Cluster B Personality Psychopathology.

Eating Recovery Center – Insight Behavioral Health **2017-2018**
Intern Clinician
Supervisors: Dr. Anne Kubal, Ph.D., Dr. Angela Derrick, Ph.D.
Conducted Acceptance and Commitment Therapy and Dialectical Behavior Therapy Skills groups and individual therapy with adults and adolescents in Intensive Outpatient and Partial Hospital programs presenting with Anorexia, Bulimia, Major Depressive Disorder, Panic Disorder, Generalized Anxiety Disorder, Obsessive Compulsive Disorder, Posttraumatic Stress Disorder, and Bipolar Disorder. Conducted extensive risk assessments for patients stepping down from inpatient hospitalization.

Indiana University Health Neuroscience Center **2016**
Practicum Clinician
Supervisor: Dr. Courtney Johnson, Ph.D., HSPP
Conducted cognitive and neuropsychological testing with adult and geriatric patients presenting with memory and psychiatric concerns, provided feedback to patients regarding testing outcomes, completed integrated assessment reports

Indiana University – Bloomington **2014-2017**
Clinician, Cognitive Behavioral Therapy Research and Training Clinic
Supervisors: Dr. Cara C. Lewis, Ph.D., HSPP and Dr. Brittany Brothers, Ph.D.
Conducted Intake Assessments (SCID; ADIS: YBOCS) and Cognitive Behavioral Therapy Individual Sessions with clients presenting with Major Depressive Disorder, Panic Disorder, Generalized Anxiety Disorder, and Specific Phobia, completed integrated assessment reports, supervised peer CBT trainees

Indiana University – Bloomington **2013-2016**
Clinician, Parent Child Clinic/Parent Behavior Training Clinic
Supervisor: Dr. John Bates, Ph.D.
Conducted Intake Assessments, completed school-based assessments, conducted Parent Behavior Training family therapy sessions for children presenting with behavior problems, completed functional analysis of child behavior, supervised peer PBT trainees

Larue Carter Memorial Hospital – Adolescent Girls and Adult Inpatient Units **2016**
Practicum Clinician
Supervisors: Dr. Melissa Butler, Ph.D., HSPP and Dr. Jenifer Vohs, Ph.D., HSPP
Conducted individual Dialectical Behavior Therapy with adult and adolescent patients with Borderline Personality Disorder, comorbid Substance Abuse, and Disruptive Mood Dysregulation Disorder, co-led Dialectical Behavior Skills Group with adolescent girls presenting with Disruptive Mood Dysregulation Disorder and emerging features of Borderline

Personality Disorder, conducted cognitive/neuropsychological screening assessments, completed integrated assessment reports

Indiana University – Bloomington **2014**

Cognitive Behavioral Therapy Research and Training Clinic Coordinator
Supervisors: Dr. Cara C. Lewis, Ph.D., HSPP and Dr. Brittany Brothers, Ph.D.

Conducted brief intake assessments and suicide risk screenings, responsible for client case assignment, case management, and case file quality assurance

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Clinical Supervision and Mentoring Experience

Indiana University – Bloomington **2015-2017**
Peer Supervisor, Cognitive Behavioral Therapy Research and Training Clinic
Supervisor: Dr. Brittany Brothers, Ph.D.
Supervised beginning Cognitive Behavioral Therapy clinicians, held ongoing supervision didactic meetings with Dr. Brittany Brothers, conducted review of therapy session videotapes, provided feedback to trainees regarding Cognitive Behavioral Therapy core competencies, rated supervision sessions for adherence and competence using the Supervision, Adherence, and Guidance Evaluation (SAGE) Rating Scale.

Indiana University – Bloomington **2014-2016**
Peer Supervisor, Parent Child Clinic/Parent Behavior Training Clinic
Supervisor: Dr. John Bates, Ph.D.
Supervised beginning Parent Behavior Training clinicians, conducted live observation of clinical sessions, rated clinicians on Parent Behavior Training adherence and competence using standardized measures.

Clinical Teaching Experience

Centerstone – Nashville, Tennessee **July 2015**
Workshop Trainer, Consultant
Topic: Measurement-Based Care
Population: Adult Mental Health Clinicians
Conducted workshop training and ongoing triweekly supervision and consultation in the application of Measurement Based Care

Wolverine Human Services – Vassar, Michigan **March 2015**
Workshop Trainer
Topic: Measurement-Based Care
Population: Adolescent Residential Mental Health Clinicians

Indiana University - Bloomington **March 2014**
Workshop Trainer
Topic: Patient Health Questionnaire-9/Measurement-Based Care

Population: Research Assistants

Research Mentoring Experience

Indiana University – Bloomington **2016-2017**
Graduate Student Honor's Thesis Mentor
Honors Student: Hannah Kassab
Project Title: The Differential Influence of Standardized versus Tailored Measurement-Based Care Training: Outcome, Predictors, and Moderators

Indiana University – Bloomington **2015-2016**
Graduate Student Honor's Thesis Mentor
Honors Student: Elena Navarro
Project Title: Who is influential? A Social Network Analysis of Measurement-Based Care Implementation

Indiana University – Bloomington **2014-2015**
Graduate Student Honor's Thesis Mentor
Honors Student: Meredith Boyd
Project Title: Key Characteristics of Mental Health Trainers: The Creation of the Measure of Effective Attributes of Trainers

General Teaching Experience

Indiana University – Bloomington **2015**
Instructor of Record: PSY-P211 Research Methods in Psychology

Indiana University – Bloomington **2012/2013**
Graduate Associate Instructor
Courses: PSY-P319 The Psychology of Personality, PSY-P350 Human Factors and Ergonomics

Leadership and Service

Elected Clinical Science Student Representative **2016-2017**
Indiana University-Bloomington

Editorial Responsibilities

Ad Hoc Reviewer
Journal of Consulting and Clinical Psychology
Cognitive and Behavioral Practice

Professional Memberships

Society for Psychotherapy Research, Member **2010-Present**

Association for Behavioral and Cognitive Therapies, Member **2012-Present**

Additional Trainings and Skills

Technical/Statistical Skills
Data Analysis in R, SPSS, MPlus
Qualitative Data Analysis in NVivo, Atlas.ti

Specialized Clinical Training – Treatment Modalities
Cognitive Behavioral Therapy (CBT)
Behavioral Activation (BA)
Exposure Therapy (Specific Phobia, Panic Disorder)
Parent Behavioral Training (Parent Management Training)
Motivational Interviewing (MI)
Dialectical Behavioral Therapy (Individual and Group DBT Skills)

Specialized Clinical Training – Assessments
American National Adult Reading Test (AMNART)
Semantic Fluency – Animals
Benson Complex Figure Copy
Boston Naming Test (BNT)
Brief Visuospatial Memory Test-Revised (BVMT-R)
Controlled Oral Word Association (COWA)
California Verbal Learning Test-Second Edition (CVLT-2)
Frontal Assessment Battery (FAB)
Finger Tapping Motor Testing
Grip Strength Motor Testing
Grooved Pegboard Motor Testing
Indiana University Tokens Test (IU Tokens)
Judgment of Line Orientation (JLO)
Multilingual Naming Test (MINT)
Mini Mental State Exam (MMSE)
Montreal Cognitive Assessment (MoCA)
Rey Auditory Verbal Learning Test (RAVLT)
Rey Complex Figure Test

Clinical Training Workshops
Dialectical Behavior Therapy Training Workshop (2017-2018)
Progressive Muscle Relaxation (2016)
Cognitive Behavioral Therapy for Insomnia (2016)
Cognitive Behavioral Therapy for Chronic Pain (2016)
Dialectical Behavior Therapy (2015)
Assertive Communication (2015)
Acceptance and Commitment Therapy (2013)
Motivational Interviewing (2013)
Mindfulness-Based Cognitive Behavioral Therapy (2013)

Administration of the Structured Clinical Interview for the DSM-IV (SCID) (2010, 2014)
Administration of the Hamilton Rating Scale for Depression (HRSD) (2010)
Cognitive Behavioral Therapy workshop administered by Julie Jacobs, Ph.D. at the University of Pennsylvania (2010)
Supportive-Expressive Dynamic Psychotherapy Workshop administered by Kathy Crits-Christoph, Ph.D. at the University of Pennsylvania (2010)

Other Professional Experience

Cornell University Atkinson Center for a Sustainable Future **2006-2009**
Ithaca, NY
Research Assistant and Intern

Tri Tech Laboratories, Inc., **2009**
Lynchburg, VA
Intern Chemist, Research and Development Laboratory

Kolmar Laboratories, Inc. **2005-2006**
Port Jervis, NY
Junior Laboratory Technician, Research and Development Laboratory